Detailed Analysis of Factors Affecting Team Success and Failure in the America's Army Game*

CASOS Technical Report

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Abstract

We analyzed an extensive data trace of the on-line multi-player first-person-shooter game America's Army to understand the traits of the social and dynamic networks present in the game. Analyses were performed at the player level, team level, and clan level. Statistical analysis methods are used to examine the data at those three levels. In addition, the dynamic social networks of the teams are examined using a variety of social network analysis methods. Particular focus is given to discovering and explaining winning strategies employed by game players. From the analyses, some ways to win the game are revealed: top America's Army players' distinct behaviors, the optimum size of an America's Army team, the importance of fire volume toward opponent, the recommendable communication structure and content, and the contribution of the unity among the team members. Also, the analyses are compared to squadlevel military research, and some similarities and differences are found.

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1. Motivation

The on-line multi-player video game America's Army has more than three million registered players. Developed by the U.S. Army, the game was designed as a recruiting and training tool to paint a realistic portrait of combat in the U.S. Army. As such it presents an opportunity to study the structure of the teams operating in a simulated combat environment, and discover what tactics and strategies they employ. Players who form winning teams must effectively use communication, cooperation, and good team behavior to be successful. We can track these teams over time and discover how their patterns of success change as they gain experience.

The following items are specific points of research we investigate:

- Organizational structures of teams and clans
- The impact of individual players on team performance
- Strategies used by players, teams, and clans
- Especially unique strategies and organizational structures employed by high-ranking teams which lead to success.

2. Raw data and initial processing

The data was recorded off of over 200 America's Army game servers over the course of 14 days. As delivered the data consisted of over 24,000 files of ASCII log files requiring 5.6 Gbytes of storage space. Each line of the log files represents one event recorded by the servers. These events describe the game statistics, where "game" is the unit for the data analysis. Each game contains two types of events: logging events and collection events. The logging events describe the teams and the players, the collection events represent actions performed by players.

- There are seven types of events used for the data analysis:
- 1. Team is initialized
- 2. Player enters the team
- 3. Weapon is used
- 4. Damage caused by the weapon
- 5. Communication between the players
- 6. Player leaves the team, scores are reported
- 7. Team finishes, outcome is recorded

There are always two teams per game playing against each other. A team can have up to 14 players. The logging event *team finishes, outcome is recorded* contains information of either the team wins or loses the game, as well as the initial and final number of players. The logging event *Player leaves the team, scores are reported* has multiple measures of the performance in the game, individual scores: leader score, wins score, objectives score, death score, kills score, ROE score, and total score. Aggregate scores can be calculated for the whole team if one aggregates the scores of the individual players playing in the team. Similarly, weapon usage and damage can be aggregated for the whole team.

Some portion of the data files ended abruptly without logical ending for the games, which caused some games to miss events of one or more types mentioned above. In cases where the

event *Team finishes*, *outcome is recorded* is missing, the game was considered to be incomplete and excluded from analysis. In cases where the event *Player leaves the team*, *scores are reported* is missing for particular players, the information about those players is not recorded. In rare occasions, some games have teams which either both have won or both have lost. We discard games where both teams won as having no reasonable explanation. If both teams lost, it means neither team satisfied the conditions to win the game, so such behavior is considered reasonable and the data was included for analysis.

Each game takes place in one of about 30 scenarios, called *missions*. Each mission has a unique 3-d environment and selection of weapons available to the players, and a unique objective each team is trying to achieve.

3. Research process

The fundamental data of the America's army project is an ASCII formatted raw log file. This file required transformation to appropriate formats for the analyses we conducted. Thus, one of the major parts in the research was storing the data in a relational database and converting the data into the DynetML format for ORA analysis. We constructed a custom parsing program to read the log files and insert the data into a database.

The social network analyses of the data were done using the ORA tool (the Organizational Risk Analyzer) [1]. The raw log files were translated to DynetML [2] format (an xml format for storing social network information) for use with ORA. The following networks were extracted and stored for analysis. The accumulated size of the DynetML files was over 15GB. The format of DynetML file used in America's Army can be found in Appendix A.

Table 1 Meta-Matrix showing networks of America's Army

	People	Knowledge	Resources	Tasks
	(Players)	(Character Ability)	(Weapon)	(Mission Objectives)
People	Social Networks	Knowledge Network	Resource Network	Assignment Network
(Players)	Report-In Network,	Soldier, Medic	Fire Trace Weapon : Normal Bullet	Objectives for
	Normal Comm.		Fire Projectile Weapon: RPG, AT4 Round, M203	Mission Accomplishment
	Network		Round	
			Throw Weapon : Grenade, Smoke	
			Grenade, Flashbang	
Knowledge		Not Used	Not Used	Not Used
(Character Ability)		There are only two kinds of knowledge.	Any player can use any weapons.	Objectives can be achieved by either medics or soldiers.
D		kinas oi knowieage.	Matthand	,
Resources			Not Used	Not Used
(Weapon)			Weapons have their own unique attributes.	Objectives are not directly
				related to weapons.
Tasks				Not Used
(Mission				There is no order for mission
Objectives)				objectives.

America's Army Raw Log File Statistical Analysis Report Database Related Programs Scenario and Game Level Analysis 1. Translate Raw Log Files Scenario Level - Team Level Player Level Communication Network Level Game and Team makeTeamStat.java RawParser.java Make general statistics
 Make 4 Report-in DynerML files according to thee direc phases
 Make 4 Normal Comm. DynerML, files according to three time phases tgreSQL Generale DynetML-Game files Player and Communication Database m PostpreSQL database ORA DynetML-Portorm Organization Risk Analysis for each DynetML file. Game file set DynetML File Sets 4 Report-In DynetML 4 Normal-Comm. DynetML Intire game, First, Second, and 1 Game) (For one game) Network Level Analysis AAVisualization.java Generated JPEG graphic files Generate visuals describing
 Damage network
 Generate visuals describing
 Report-in network Visualization of Damage and Communication Networks Damage Network Presentation Generate visuals describing
 Normal Comm. network Communication **Netwrok Presentation**

Figure 1 America's Army Research Process Diagram

Research results were produced by four-step research process:

- 1. Data Mining from Relational Database
- 2. Traditional statistic analysis
- 3. Dynamic network analysis using ORA
- 4. Statistic analysis of the data mining, common statistic data, and ORA results

4. Database processing

In order to eliminate multiple time consuming parsing of the data from large amount of files (~24,000), the data was inserted in a relational PostgreSQL database. This allows a particular analysis of the data can be obtained by querying the database instead of parsing of the content of all files. 11 tables were created, and followings are the ER-diagram specifying the database structure.

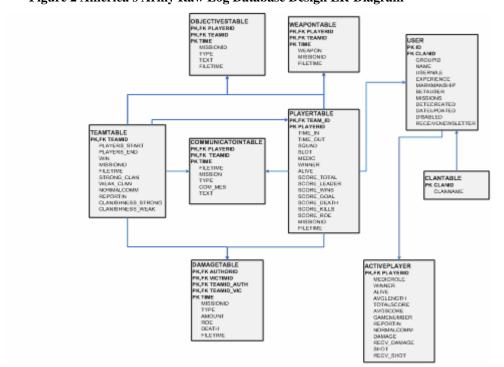


Figure 2 America's Army Raw Log Database Design ER-Diagram

5. Data Analysis

Table 2 presents some summary data on the dataset.

Table 2 Brief summary of America's Army dataset

Description	Number	Description	Number
Sampled teams	491750	Sampled players	73497
Logging game events	3044599	Communication events	8184020
Weapon usage events	66968404	Damage events	15047745
Registered Users	3402714	Parsed clan names	278155

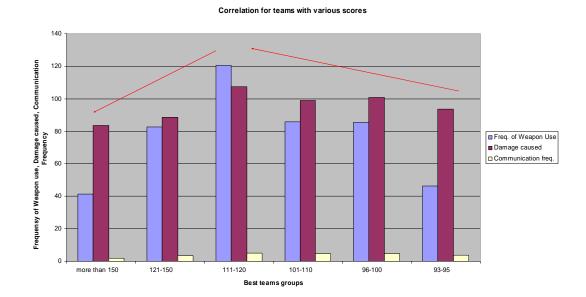
The data was analyzed at three levels: players, teams, and clans. A clan is a social group of players created informally among the players, which tends to persist over a long time period. As stated in the motivation, the major concern of this project is understanding the behavior of the players at the team level so particular attention is given to the team level analysis, but the data analyses on the player and clan levels also give some insights to the team level behavior, so those levels were analyzed as well.

5.1. Definition of a performance measure and methodology to construct communication network for data analyses

5.1.1. Anomalies in the original score of America's Army and a new performance measure

During data analysis on the America's Army dataset, it was noticed that the average total score did not correlate well with actually winning the game. When the 1606 teams having highest average total score were sorted and graphed, in Figure 3, we noticed that frequency of weapon use, damaged caused, and communication frequency increase when the average score of the best teams group goes from 110 to 120 and then goes down when the average score is over 120.

Figure 3 Bar graph showing frequency of weapon usage, damage caused, and communication frequency with 1606 teams having top average total scores



This indicates that average total score might not be the most appropriate team performance measure. Therefore, the team level average total score was investigated further. The team level average total score is the average of total score obtained by individual team members, and the team members' total score is a weighted summation of 6 different scores: leader score, wins score, goal score, death score, kills score, and ROE (rules of engagement) score. The scores of the top 1000 players sorted by the average total score are graphed in Figure 4. This graph shows that leader score, wins score, goal score, and kills score increase as total score increases. However, ROE score and death score do not show a consistent trend with respect to the total score. Therefore we conclude that those measures add noise to the total score.

This analysis suggested that we needed to create a new measure of team performance. The new performance measure was created using a linear regression model to predict the likelihood of winning the game. Below is the detailed formula of the new performance measure. In Table 3, it can be seen that the coefficients for ROE score and death score are extremely low, indicating the new performance measure minimizes their influence. At the same time, Figure 5 shows the wins score and the survival ratio exhibit a relatively strong influence on winning.

New_score = a0 + a1*score_leader + a2*score_wins + a3*score_goal + a4*score_death + a5*score_kills + a6*score_roe + a7*survive_ratio(friendly_players) + a8*survive_ratio(enemy_players)

Table 3 Coefficient values to calculate new performance measure

Coefficient	Value
a0	0.524254
a1	0.00014
a2	0.004143
a3	0.002394

a4	0.00091
a5	-0.01036
a6	1.25E-05
a7	0.619807
a8	-0.68754

Figure 4 Bar graph illustrating decomposed scores from total score with top 1000 players

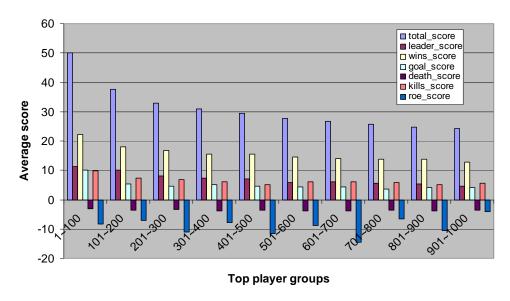
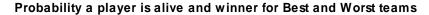
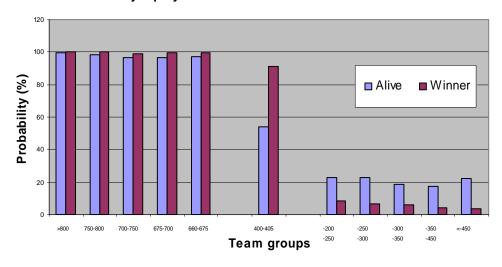


Figure 5 Bar graph displaying percentage of winning and survival for teams sorted with new performance measure

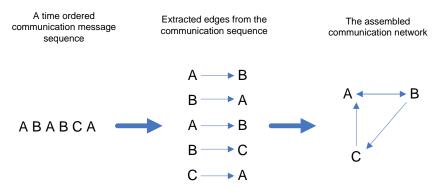




5.1.2. Communication Network Analysis

ORA was used to analyze aspects of the dynamic and social networks present in the game. In the America's Army project, players communicate several types of messages with each others during game play, and this communication relationship can be interpreted as a sort of social networks. However, the communication messages are always broadcast to the entire team, not to a specific team member, so a heuristic to assemble a person to person social network from those messages. We used a "who-talks-after-whom" to create these networks (see Figure 6).

Figure 6 Example of the Who-talks-after-whom Heuristic



(A, B, and C represents players who broadcasted a communication message.)

There are several types of communications: Commo, TeamSay, Whisper, and Report-In. In this project, those communications are classified into two categories: Normal Communication and Report-In Communication. In Normal communication, the player can type any message any message on the keyboard to send to the team, or he can pick from several pre-defined messages. In Report-In communication, the player presses a special hot-key which sends that player's location on the map to the other players.

5.2. Player level data analysis

5.2.1 Top 100 players, middle 100 players, and bottom 100 players

Players' game play style varies widely, and their different styles result in different performances during game play. Thus, to figure out the play style of the winners, some statistical analyses were conducted on three categories of players. The three player categories are top player category, middle player category, and bottom player category. The standard for the category is the average total score of each player, and for each category, 100 players are selected. The population is restricted to players who played more than 10 games in the given data set.

Table 4 The selected players to represent the three player categories: 100 top players, 100 middle players, and 100 bottom players. The count of distinct players who played more than 10 games is 53725. The index for ordering is the average total score for each.

	From	То
Top player category	1st player	100th player
Middle player category	26812nd player	26911st player

Bottom player category	53726th player	53725th player
2 3 11 3 11 7 11 7 11 7 11 7 11 7 11 7 1	00, = 0011 p100, 01	0 0 7 = 0 til plug 01

Figure 7 shows the weapon usage by the three player categories. The most frequently used weapons vary across the top players. 16 weapons are selected by 100 top players, and the first, the second and the third most frequently chosen weapon by the top players are M4A1 Rifle, M16A2 Rifle, and M67 Frags, respectively. Also, M9 Pistol and SPR Sniper Rifle are selected as the most frequently used weapons only by top players.

In Figure 7 and Figure 8, there are slight different in the usage of weapons. Like top players, middle players frequently use M4A1 and M16A2, but the middle also players also frequently use AK74su rifle. The number of middle players who chose the AK74su as the favorite weapon is 22, but the number of top players who chose the rifle is 7. Additionally, among bottom players sniper rifles are not represented at all, and the frequency for M4A1 is very limited: only 10 players chose M4A1 as their favourite weapon. This is most likely due to the high level of training that the game requires before a player is allowed to use these weapons.

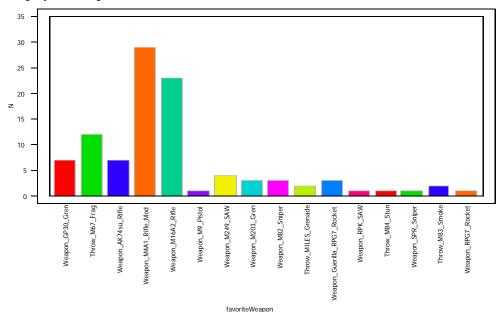


Figure 7 Top 100 players' weapon selection.

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Figure 8 Middle 100 players' weapon selection.

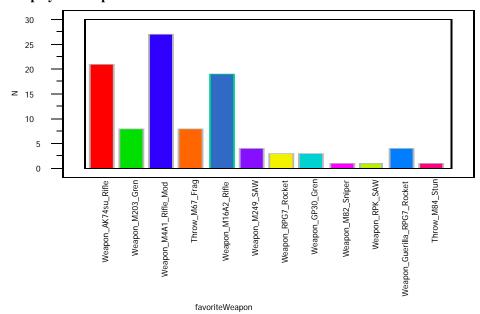
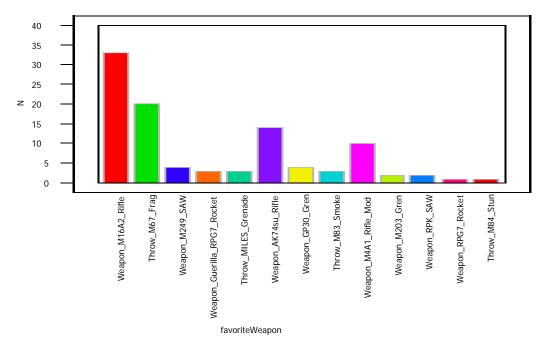


Figure 9 Bottom 100 players' weapon selection.



Figures 10-12 show scatter comparing the average Normal Communication and the average Report-In communication for each player category. In Figure 10, the scatter plots for the top players, many points are located in the area which is over 4 average Report-In communications per game. On the other hand, for the middle players, in Figure 11, there are three points which have over four Report-In communications, and for the bottom players, Figure 12, only two points exist in this area. It clearly shows that the top players tend to report their position to the team members more frequently.

For normal communication, the three categories do not show such as significant a difference as report-in communication. The top players tend to communicate through the normal communication, but among the middle players and the bottom players, there are players who communicate with team members very frequently.

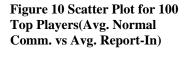
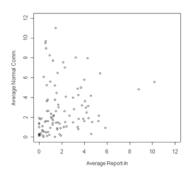
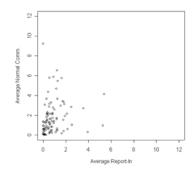
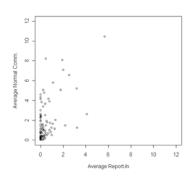


Figure 11 Scatter Plot for 100 Middle Players(Avg. Normal Comm. vs Avg. Report-In)

Figure 12 Scatter Plot for 100 Bottom Players(Avg. Normal Comm. vs Avg. Report-In)







In addition, with Figure 13, 14 and 15, it is obvious that the top players are much better in damage management than the middle players and the bottom players. In Figure 13, there are no top players who take more than 85 damage events per game, and there are 4 players who take less than 20 damage events. On the contrary, many middle and bottom players take more than 85 damage events, and only a small number of the middle players and the bottom players take less those 40 damage events.

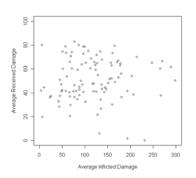
The amounts of damage events inflicted on the opponent also illustrate differences among the three categories. The top players are likely to inflict large amount of damage and to get small amount of damage at the same time. They do not necessarily receive more damage even though they are more aggressive. For example, in Figure 13, there are players who inflict more than 250 damage events while receiving 30~70 damage events. However the middle and the bottom players have a slight positive relationship between average damage received and average damage inflicted. This means that if the middle and the bottom players become more aggressive, they also become more vulnerable. For example, in Figure 14, the middle players who inflicted more than 100 damages events generally take more than 50 damage events.

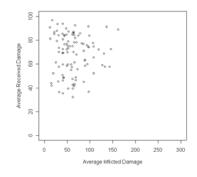
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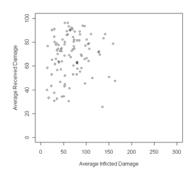
Figure 13 Scatter Plot for 100 Top Players(Avg. Received Damage vs Avg. Inflicted Damage)

Figure 14 Scatter Plot for 100 Middle Players(Avg. Received Damage vs Avg. Inflicted Damage)

Figure 15 Scatter Plot for 100 Bottom Players(Avg. Received Damage vs Avg. Inflicted Damage)



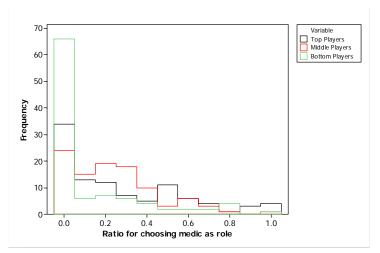




The role selections in the game show minor differences among the three categories. Currently there are only two roles a player can pick from: medic and soldier. In Figure 16, the histogram shows clearly that the bottom players tend to select soldier as their role in the game and that the top players are likely to keep selecting only medic or only soldier. For instance, in Figure 16, more than 60 bottom players selected only the soldier role. The top players show different tendency in the role selection. 35 top players keep selecting only soldiers, 5 top players keep selecting only medics, and 15 top players selects both roles roughly equally. It seems that there are some top players who are specialized in playing as medic or soldier, and there are also top players who can perform both roles successfully.

While the top players and the bottom players choose their roles somewhat consistently, the middle players usually choose soldier as their roles and occasionally select medic. Thus, there are only about 25 middle players who keep selecting soldiers and no middle players who keep picking medic.

Figure 16 Histogram for ratio of choosing medic as role



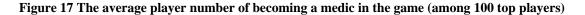
5.2.2 Outlier analysis among top 100 players

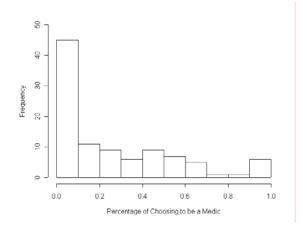
We have identified statistical outliers among top players along various axes that we have analyzed. These outlying players are dissimilar to the other top players, even though they are all doing excellent in the game. Thus, the investigation of the outliers is a good first step to identify different ways for players to succeed in the game.

5.2.2.1 Medic specialized top players

Figure 17 shows that some of the top players almost always choose to be a medic. The percentage of becoming a medic generally keeps decreasing from 0% to 90%, but the frequency of percentage between 90 and 100% is almost 10%, meaning that there are approximately 10 top players who almost always become medics. Considering most top players usually choose to be a soldier and only occasionally a medic, these outlying top players might have developed their own strategy to succeed as a medic.

Figure 18 shows some differences between typical top players and top players who prefer to choose the medic role. It suggests that the medical outliers' chance to survive is lower than the typical top players'. At the same time, the medical outliers' numbers of shots and received shots are lower than the typical top players', but their received damage is higher than the typical players. In other words, they were shot at fewer times than the typical top players but they received more damage. Thus the medic specialized players are more easily damaged by opponents. Additionally, the medic outliers transmit the Report-In communications more frequently than the typical top players. It seems that the medic specialized top players want to broadcast their location more often than the typical top players do. Perhaps this is a strategy to allow other players to know their location so that they can receive medical assistance more quickly. This could tend to improve overall team performance.





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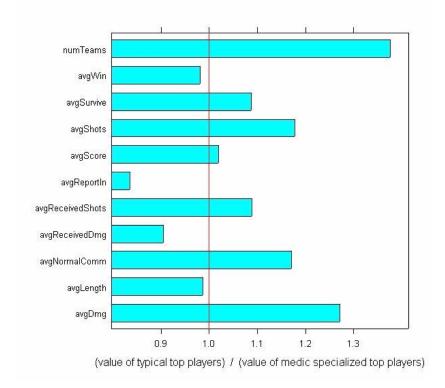


Figure 18 Comparison between typical top players and medic specialized top players

5.2.2.2 Frequent Report-In top players

Figure 19 suggests another group of outliers among the 100 top players. While most top players don't seem to transmit Report-In communication more than 6 times per one game, there are less than 5 players who communicate through Report-In communication much more frequently than other top players do.

In figure 20, the frequent Report-In top players are compared to the typical top players. The Report-In outliers' chance to survive is much lower than the typical players'. However, the Report-In outliers exceeds the typical top players in shots, received shots, damage, received damage, frequency of Normal Communication, and the frequency of Report-In communication. In other words, except the chance to survive, the Report-In outliers have higher values in almost all the other attributes than the typical top players have. This suggests that they generally play much more actively than the typical players do.

Figure 19 the average number of transmitting the given number of Report-In communication (amoung 100 top players)

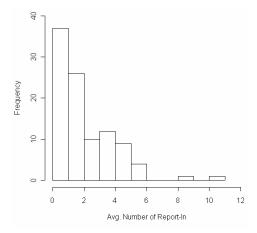
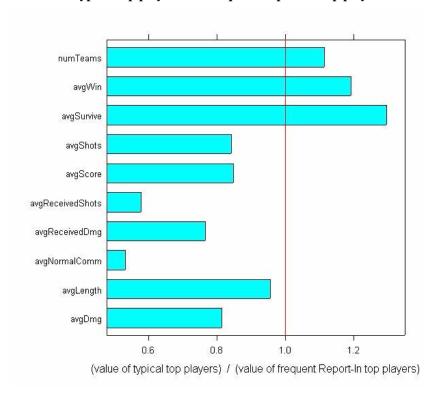


Figure 20 Comparison between typical top players and frequent Report-In top players



It is obvious that the frequent Report-In top players are among the most active players, and their play style might create greater success. To analyze and understand their play we have looked at their individual actions during the game. The one outlying player who used Report-In communication more than 10 times was extracted from the data, and his play style in one game was visualized as three who-talked-after-whom Report-In networks in figures 21 to 23. There are three images because the Report-In who-talked-after-whom network is divided into three time segments.

According to the Report-In who-talks-after-whom networks, it is very noticeable that the networks always start from the frequent Report-In top players. If the Report-In outlier transmitted his Report-In while the others were reporting, there should be an arrow starting from him to the other team members. However such an arrow is not there. This means that he transmitted his Report-In repeatedly until the other team members transmit their Report-In. After the other team members start Report-In, he didn't transmit his Report-In. It seems that he is requesting the other team members to broadcast their Report-Ins, and that behaviour can be interpreted as the behaviour of the combat leader.

Figure 21 observing the frequent Report-In top player's play (1) (The outlying player is the player in the red box.)

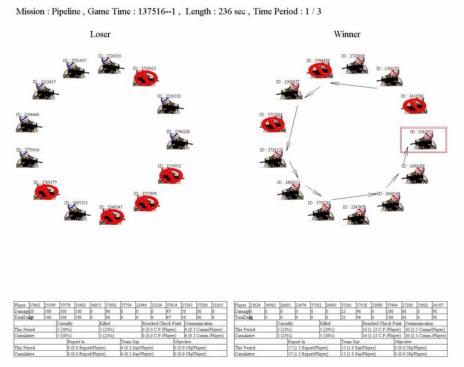


Figure 22 observing the frequent Report-In top player's play (2) (The outlying player is the player in the red box.)

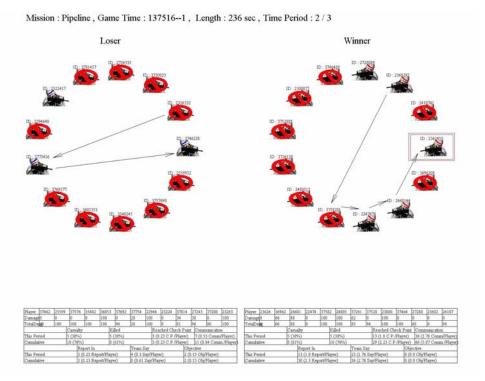
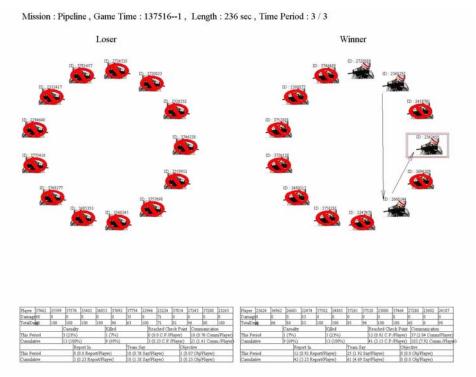


Figure 23 observing the frequent Report-In top player's play (3) (The outlying player is the player in red box.)



5.3. Team level data analysis

5.3.1 Overall team level statistics and interpretation

Table 5 shows that as the team size increases, the survival rate for the winning team goes down, reaching the minimum at size 13. The reason is that the small teams suffer more from a single loss of a player and can easily become a losing team with only a few lost players. Therefore the majority of small-size winners have relatively small losses. However for larger teams losing a few players makes less of a difference. The different result for size 14 (the survival rate grows from the team of size 13 to the team of size 14) is probably due to the low number of teams of that size, so the data is less representative. The survival rate for the losing teams, on the contrary, goes up for the teams from size 1 to size 10. Then the survival ratio drops rapidly when the team size grows from 10 to 14. The absolute values of the average number killed/survived players for the teams of different sizes are shown in Figure 24.

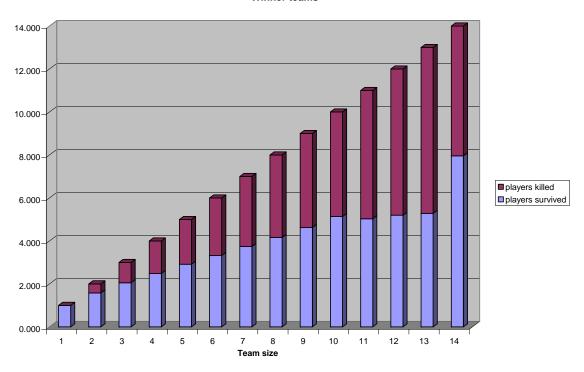
Table 5 Average initial number of players ("Avg start"), average resulting number of players ("Avg end"), average number of players killed ("Avg killed"), and average survival rate for teams of different sizes (1 to 14) for teams which have won ("Winner") and have lost ("Loser").

	Winner				Loser			
	Avg	Avg	Avg	Survival	Avg	Avg	Avg	Survival
Team size	start	end	killed	%	start	end	killed	%
size=1	1.000	0.998	0.002	99.8	1.000	0.045	0.955	4.5
size=2	2.000	1.581	0.419	79.1	2.000	0.138	1.862	6.9
size=3	3.000	2.055	0.945	68.5	3.000	0.272	2.728	9.1
size=4	4.000	2.482	1.518	62.1	4.000	0.443	3.557	11.1
size=5	5.000	2.913	2.087	58.3	5.000	0.657	4.343	13.1
size=6	6.000	3.319	2.681	55.3	6.000	0.830	5.170	13.8
size=7	7.000	3.741	3.259	53.4	7.000	1.052	5.948	15.0
size=8	8.000	4.158	3.842	52.0	8.000	1.432	6.568	17.9
size=9	9.000	4.622	4.378	51.4	9.000	1.783	7.217	19.8
size=10	10.000	5.134	4.866	51.3	10.000	2.343	7.657	23.4
size=11	11.000	5.030	5.970	45.7	11.000	1.130	9.870	10.3
size=12	12.000	5.194	6.806	43.3	12.000	1.166	10.834	9.7
size=13	13.000	5.280	7.720	40.6	13.000	0.653	12.347	5.0
size=14	14.000	7.957	6.043	56.8	14.000	0.101	13.899	0.7
size<4	1.914	1.487	0.427	77.7	1.755	0.132	1.623	7.5
size>5 & size<9	6.059	3.347	2.712	55.2	6.051	0.899	5.152	14.9
size>8	10.140	4.993	5.147	49.2	10.088	1.868	8.220	18.5

Table 6 presents the team metrics for different missions. The winning teams have a relatively constant survival rate for all missions: between 45-65%. The losing teams have decent survival rate for some missions (SFhospital: 44.8%, Mountain_Ambush: 27.5%), but for the majority of missions the loser teams had a survival rate below 10%. The other noticeable result is that different missions have different team sizes. Whereas such mission as SFhospital, Pipeline, SFstorm, Mountain_Pass have the average team size 7 and up, other missions: Tunnel, JRTC_Farm, Swamp_Raid, HQ_Raid, have the average team size below 5. The choice of the team size probably depends on the mission goals and geographical layout.

Figure 24 Average number of killed/survived players for Winner/Loser teams





Loser teams

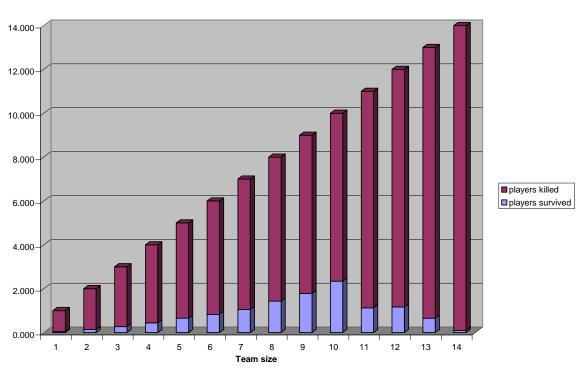


Table 6 The total number of teams for each mission ("Teams"). Average initial number of players ("Avg start"), average resulting number of players ("Avg end"), average survival rate ("Survive %"), the maximum ("MAX"), and the minimum ("MIN") sizes of the teams

		Winner					Loser				
Minaton	0	Ave	Ave	Survive	MAY		Ave	Ave	Survive	14 A V	NAIN!
Mission	Games	start	end	%	MAX	MIN	start	end	%	MAX	MIN
Pipeline	17,828	7.31	3.33	45.6	13	1	7.17	0.37	5.2	13	0
Pipeline_SF	12,959	6.08	2.91	47.9	13	1	5.92	0.29	4.9	13	0
SFvillage	7,836	5.91	2.74	46.4	13	1	5.74	0.11	1.9	13	0
SFarctic	8,301	5.74	2.89	50.3	13	1	5.58	0.48	8.6	13	0
MOUT_McKenna	22,872	5.39	2.80	51.9	9	1	5.23	0.4	7.6	9	0
SFhospital	57,580	7.24	4.72	65.2	13	1	7.17	3.21	44.8	13	0
Bridge	21,349	5.96	2.97	49.8	13	1	5.81	0.09	1.5	13	0
Bridge_SE	5,816	5.65	3.04	53.8	13	1	5.45	0.41	7.5	13	0
Insurgent_Camp	23,030	6.44	3.28	50.9	13	1	6.25	0.45	7.2	13	0
Weapons_Cache	16,510	5.51	2.64	47.9	13	1	5.36	0.02	0.4	13	0
Weapons_Cache_SE	4,677	6.31	2.84	45.0	13	1	6.18	0.06	1.0	13	0
SFrecon	730	4.59	2.75	59.9	10	1	4.39	0.5	11.4	10	0
Sfcsar	12,924	6.95	3.23	46.5	11	1	6.81	0.17	2.5	11	0
SFsandstorm	8,058	7.05	3.43	48.7	10	1	6.87	0.73	10.6	10	0
HQ_Raid	2,783	4.28	2.66	62.1	9	1	4.05	0.14	3.5	9	0
Radio_Tower	1,849	7.55	3.52	46.6	13	1	7.35	0.16	2.2	13	0
River_Basin	1,839	5.30	2.92	55.1	13	1	5.07	0.19	3.7	13	0
Mountain_Pass	3,576	7.00	3.91	55.9	13	1	6.78	0.49	7.2	13	0
Mountain_Pass_SE	1,359	6.49	3.20	49.3	13	1	6.29	0.73	11.6	13	0
Mountain_Ambush	1,902	6.85	4.04	59.0	12	1	6.66	1.83	27.5	12	0
Tunnel	5,194	3.54	2.18	61.6	8	1	3.37	0.27	8.0	8	0
Swamp_Raid	1,273	4.09	2.33	57.0	9	1	3.89	0.56	14.4	9	0
FLS	2,804	6.86	4.04	58.9	14	1	4.73	0.46	9.7	14	0
JRTC_Farm	625	3.66	2.26	61.7	8	1	3.44	0.12	3.5	8	0
Total	243,674	5.91	3.11	53.21	11.8	1.0	5.65	0.51	8.60	11.8	0.0

Tables 7 to 14 show aggregate scores for teams of different sizes. These aggregate scores are obtained from the scores of the individual players of each teams. The common feature of the results is that the values of standard deviations are higher than the average values; therefore these results are trends rather than statistically significant results. Table 7 presents total scores. It should be noted that, for all score-related tables, the results for the teams having more than 10 players are less reliable due to lower number of teams (fewer than 5,000). The number of teams with less than 11 teams is never smaller than 16,000. We also notice that the highest number of teams and players are for teams of size 10, so that size is the most popular. The final observation is that the winning teams have the highest average total scores when the team size is 10. The losing teams have the lowest average total scores when the team size is 9. This result is also supported by Figure 25, which presents this data graphically.

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Table 7 Average, Standard Deviation, Maximum, Minimum values of TOTAL SCORE for Winner and Loser teams, Total number of teams and players for different Team sizes.

Team										
Size	Winner	Total Sco	re		Loser	Total Score				
									# of	# of
	Average	StdDev	Max	Min	Average	StdDev	Max	Min	teams	players
1	2.64	22.47	280	-840	-4.57	29.44	340	-1540	19,853	19,744
2	14.39	58.96	1434	-900	-13.67	61.41	429	-1940	16,455	32,451
3	26.89	72.76	629	-1137	-16.54	66.51	373	-1220	17,370	51,380
4	25.63	79.87	540	-1112	-18.01	68.78	369	-2132	22,521	88,675
5	26.84	85.53	1014	-1612	-18.18	71.43	583	-1856	20,685	101,458
6	27.03	83.73	545	-3514	-18.11	71.11	867	-1482	23,595	139,057
7	24.57	88.60	460	-1872	-18.73	71.98	400	-1548	19,249	132,432
8	25.71	89.53	469	-2136	-20.29	76.38	680	-2202	26,081	205,693
9	24.59	92.22	644	-2204	-21.41	79.75	470	-2220	24,370	215,776
10	30.01	84.47	548	-1350	-19.97	78.01	531	-2922	32,214	316,099
11	21.82	79.38	442	-1192	-14.71	69.05	391	-3000	4,695	50,666
12	21.37	81.72	424	-1216	-15.67	71.74	383	-2445	7,223	84,942
13	20.11	75.93	392	-1640	-13.74	67.83	364	-2096	3,748	48,019
14	13.8	46.29	235	-665	-6.58	30.6	140	-388	89	1,230

Table 8 Average, Standard Deviation, Maximum, Minimum values of NEW SCORE for Winner and Loser teams for different Team sizes.

Team Size	Winner	New Sco	re		Loser	New Scor	e	
	Average	StdDev	Max	Min	Average	StdDev	Max	Min
								-
1.00	534.98	80.41	3101.77	-69.73	25.26	160.77	788.42	2808.76
2.00	485.23	116.44	1051.31	-581.06	7.39	114.11	620.80	-667.16
3.00	466.98	122.54	930.84	-370.53	41.13	111.63	710.57	-709.85
4.00	440.58	121.28	815.83	-473.75	65.40	107.04	638.21	-745.28
5.00	421.43	117.60	807.07	-367.06	82.77	105.43	611.70	-581.46
6.00	409.85	112.94	801.93	-296.03	93.99	103.15	651.05	-540.40
7.00	396.50	116.23	805.26	-321.98	101.21	100.58	573.45	-472.28
8.00	389.22	112.22	796.08	-398.64	114.00	99.94	575.18	-556.86
9.00	375.66	112.14	779.95	-336.17	117.44	100.32	510.09	-488.95
10.00	377.96	107.32	733.41	-387.22	131.65	99.21	488.60	-515.85
11.00	379.30	100.12	722.42	-171.43	116.47	90.41	536.19	-341.04
12.00	379.49	96.47	715.96	-341.11	123.64	87.12	480.04	-360.98
13.00	377.99	88.59	687.58	-145.72	122.44	81.82	504.27	-144.00
14.00	392.64	95.68	596.16	114.75	80.64	91.52	375.64	-86.04

Table 9 Average, Standard Deviation, Maximum, Minimum values of LEADER SCORE for Winner and Loser teams for different Team sizes.

Team								
Size	Winner	Leader Sco	re		Loser	Leader Sco	re	
	Average	StdDev	Max	Min	Average	StdDev	Max	Min
1	-0.19	4.01	80	-180	-0.26	4.30	45	-150
2	1.8	12.50	80	-290	-2.49	10.83	70	-390
3	3.99	18.33	90	-340	-3.27	13.62	70	-450
4	4.73	23.19	130	-470	-3.7	15.34	70	-450
5	6.73	28.28	130	-490	-4.77	17.31	70	-515
6	7.05	28.81	130	-490	-4.76	17.89	70	-570
7	6.48	31.44	140	-590	-4.75	18.79	70	-550
8	6.7	31.69	150	-660	-4.81	20.13	70	-630
9	6.34	33.18	170	-720	-4.92	21.81	70	-730
10	7.27	32.85	180	-690	-4.75	21.70	70	-810
11	5.84	30.01	150	-600	-3.72	17.97	70	-590
12	5.73	30.65	170	-810	-3.93	18.88	70	-670
13	5.99	28.31	150	-610	-3.24	15.45	70	-600
14	4.27	23.04	108	-465	-2.81	11.59	15	-235

Table 10 Average, Standard Deviation, Maximum, Minimum values of WINS SCORE for Winner and Loser teams for different Team sizes.

Team					_			
Size	Winner	Wins Score			Loser	Wins Score		
	Average	StdDev	Max	Min	Average	StdDev	Max	Min
1	-0.93	11.20	50	-390	-1.46	13.34	1	-420
2	8.56	35.45	60	-420	-6.20	28.49	1	-390
3	18.93	43.35	60	-410	-8.92	35.32	1	-420
4	18.04	47.30	60	-390	-9.64	36.67	1	-420
5	17.71	47.68	60	-350	-9.54	36.39	1	-420
6	18.26	46.04	60	-360	-9.66	36.88	1	-550
7	16.71	50.50	60	-1850	-10.41	38.32	1	-420
8	18.49	50.18	60	-390	-10.85	39.70	1	-360
9	18.13	52.90	60	-1200	-12.02	42.65	1	-360
10	21.65	49.46	60	-360	-10.93	41.30	1	-360
11	14.84	37.97	60	-390	-7.23	30.11	1	-360
12	14.74	38.58	60	-350	-7.36	30.64	1	-360
13	13.21	29.25	60	-350	-4.92	21.55	0	-390
14	9.18	21.74	20	-140	-3.76	15.66	0	-120

Table 11 Average, Standard Deviation, Maximum, Minimum values of OBJECTIVES SCORE for Winner and Loser teams for different Team sizes.

Team								
Size	Winner	Objectives :	Score		Loser	Objectives :	Score	
	Average	StdDev	Max	Min	Average	StdDev	Max	Min
1	-0.13	3.66	100	-240	-0.3	5.28	40	-260
2	1.23	11.58	100	-320	-0.41	9.92	80	-260
3	2.41	14.72	120	-380	-0.53	11.95	114	-380
4	2.26	14.69	155	-484	-0.55	12.23	135	-400
5	2.36	15.83	180	-620	-0.47	13.72	160	-460
6	2.23	14.26	220	-430	-0.47	12.92	180	-550
7	1.98	13.21	121	-265	-0.61	11.09	96	-329
8	2.05	13.43	135	-225	-0.65	11.00	125	-235
9	1.69	13.24	120	-346	-0.85	12.12	122	-310
10	2.79	13.64	133	-305	-0.59	12.17	120	-320
11	2.45	15.47	99	-425	-0.23	14.50	109	-309
12	2.54	17.10	116	-355	-0.2	14.18	120	-326
13	3.27	17.21	119	-263	0.13	15.84	106	-339
14	0.42	6.82	59	-160	0.57	7.09	49	-112

Table 12 Average, Standard Deviation, Maximum, Minimum values of DEATH SCORE for Winner and Loser teams for different Team sizes.

Team Size	Winner	Death Score			Loser	Death Score		
Size	Average	StdDev	Max	Min	Average	StdDev	Max	Min
1	1.31	7.13	90	-10	-5.75	11.14	70	-10
2	0.83	10.56	70	-10	-5.08	12.53	70	-10
3	0.36	12.06	80	-10	-4.69	13.19	70	-60
4	0.11	12.74	70	-10	-4.45	13.36	75	-330
5	-0.12	13.03	70	-80	-4.25	13.41	100	-200
6	-0.54	12.87	70	-85	-4.23	13.51	360	-200
7	-0.4	13.39	230	-300	-3.86	13.81	70	-160
8	-0.76	13.05	70	-77	-3.79	13.54	70	-260
9	-0.5	13.49	220	-10	-3.38	13.87	70	-110
10	-1.26	12.44	70	-150	-3.84	12.63	70	-220
11	-1.47	13.15	70	-10	-4.47	13.87	70	-10
12	-1.47	13.68	70	-202	-4.68	13.65	70	-10
13	-2.37	12.71	70	-10	-5.36	13.51	70	-10
14	-1.93	9.56	70	-10	-7.33	9.13	60	-10

Table 13 Average, Standard Deviation, Maximum, Minimum values of KILLS SCORE for Winner and Loser teams for different Team sizes.

Team								
Size	Winner	Kills Score			Loser	Kills Score		
	Average	StdDev	Max	Min	Average	StdDev	Max	Min
1	4.61	11.13	50	-200	-1.06	9.45	30	-140
2	3.66	15.73	50	-200	-0.74	12.83	50	-180
3	3.7	17.67	60	-240	-0.44	14.77	50	-220
4	3.22	18.73	70	-260	-0.16	15.59	80	-210
5	3.09	19.58	90	-340	0.18	16.26	80	-290
6	3.27	19.33	110	-260	0.36	16.50	110	-340
7	2.78	20.14	80	-470	0.34	16.82	70	-270
8	2.91	19.41	80	-250	0.52	16.60	70	-250
9	2.45	19.80	100	-320	0.4	16.96	80	-260
10	3.09	18.53	100	-290	0.99	16.08	80	-240
11	3.32	21.09	100	-270	0.99	18.28	100	-230
12	3.45	21.58	100	-270	1.23	18.46	100	-290
13	4.32	20.88	110	-260	1.7	18.07	100	-260
14	1.71	11.51	50	-120	0.77	9.45	40	-160

Table 14 Average, Standard Deviation, Maximum, Minimum values of ROE SCORE for Winner and Loser teams for different Team sizes.

Team								
Size	Winner	ROE Sco	re		Loser	ROE Score	•	
	Average	StdDev	Max	Min	Average	StdDev	Max	Min
1	-2.41	117.41	3,780	-8,400	-5.47	222.72	3,600	-15,400
2	-4.62	270.31	15,240	-6,920	-41.61	561.21	4,390	-29,000
3	-14.51	348.00	6,690	-19,200	-32.63	487.23	5,010	-15,700
4	-17.53	375.42	6,500	-18,140	-36.44	489.60	4,040	-19,820
5	-20.06	400.46	10,440	-16,120	-38.21	505.95	6,830	-28,160
6	-24.56	413.86	5,300	-35,140	-36.08	490.55	9,570	-15,800
7	-22.62	428.87	4,000	-14,980	-33.39	502.21	3,980	-19,080
8	-30.89	460.60	5,900	-23,060	-44.67	548.02	7,000	-25,620
9	-28.75	476.66	6,580	22,040	-40.63	549.57	5,780	-25,800
10	-31.32	441.83	7,200	-17,000	-43.25	531.13	5,210	-29,220
11	-31.96	438.68	3,970	-12,260	-40.32	519.97	3,980	-28,700
12	-35.60	467.73	3,980	-11,960	-47.33	552.94	3,980	-23,320
13	-47.02	491.58	3,840	-18,360	-64.40	587.61	3,940	-21,560
14	-10.82	173.62	2,500	-2,960	-5.83	197.33	3,950	-3,880

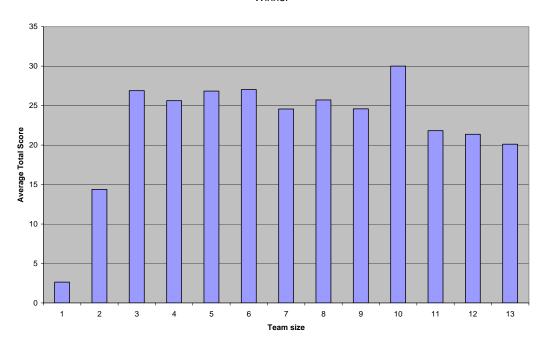
5.3.2 Weapon usage analysis

Each mission has a particular set of weapons available to the players. In this section we look at how this weapon usage (type and frequency) affects the game outcome for particular missions. To answer this question, the weapon usage was analyzed for different weapon types. Table 15 shows how many times each weapon was used by winning and losing teams. There is a noticeable difference between weapon usage for winning and losing teams. Averaging over all types of weapons, the winners use any weapon 1.22-1.34 times more often than the opponents. This suggests that in general more frequent weapon usage contributes to the success in the game.

The choice of the weapon types also affects the game outcome. For example, the usage of RPG7_Rocket (624 by winners against 180 by losers) affects the game outcome significantly stronger than M9_Pistol (55,208 by winner against 54,868 by losers). To show these distinctions between different weapon types quantitatively, the data from table 15 are presented in table 16, which shows the winner/loser ratios of the weapon usage. There are three groups of weapon types with respect to the team size. One group consists of the weapon types, in which the winner/loser ratios of the weapon usage are higher if the team size is small. This means that a weapon of this type has higher impact if the team is small than if the team is large. The data for this group is presented on figure 27. A smaller group consists of the weapon types in which the winner/loser ratios of the weapon usage are higher if the team is large. This data is presented in figure 28. The rest of the weapon types do not show any dependence on the team size.

Figure 25 Average Total score for Winner/Loser teams of different size

Winner



Loser

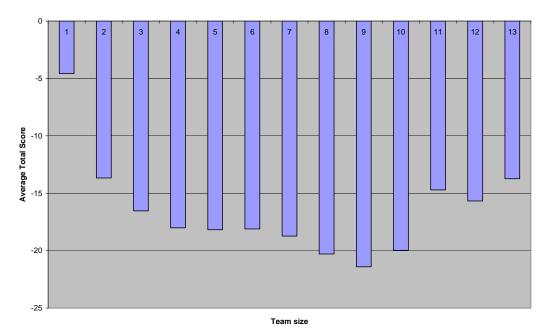
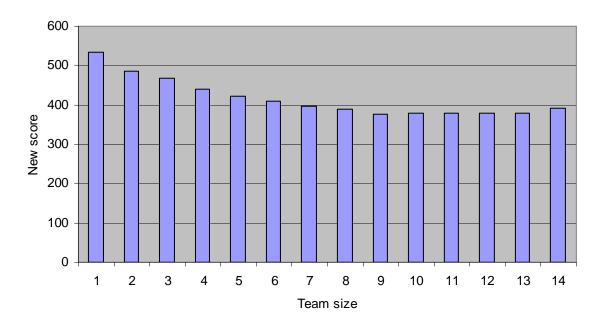


Figure 26 New score for Winner/Loser teams of different size

Winner



Loser

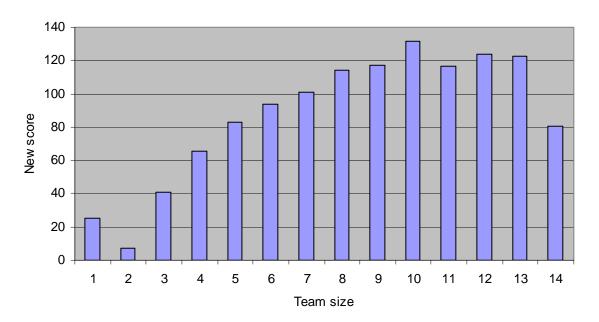


Table 15 Number of times each type of weapon has been used for Winner and Loser teams for large (more than 8), medium (between 4 and 9), and small (less than 5) size teams

	All teams		Team size:	>8	9>TeamSiz	ze>4	Team size	e<5
	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser
Weapon name	Team	Team	Team	Team	Team	Team	Team	Team
Weapon_M203_Gren	1,276,192	1,034,072	657,973	517,734	373,858	327,000	244,361	189,338
Weapon_M249_SAW	11,522,934	9,742,712	5,244,881	4,209,659	4,394,517	3,983,971	1,883,536	1,549,082
Weapon_M16A2_Rifle	6,645,619	4,861,095	3,152,149	2,234,106	2,506,391	1,921,663	987,079	705,326
Throw_M84_Stun	141,852	111,322	73,538	56,882	51,005	40,544	17,309	13,896
Throw_M67_Frag	384,877	310,754	167,141	131,928	161,558	131,314	56,178	47,512
Weapon_RPK_SAW	3,146,254	2,292,667	1,828,121	1,377,232	1,116,958	790,423	201,175	125,012
Throw_M83_Smoke	185,549	172,231	97,923	92,361	67,919	61,478	19,707	18,392
Weapon_GP30_Gren	64,082	29,477	34,940	17,784	21,512	8,677	7,630	3,016
Weapon_AK47_Rifle	206,006	112,661	87,274	51,844	89,786	47,549	28,946	13,268
Weapon_M4A1_Rifle_								
Mod	11,197,991	8,631,434	5,610,768	4,476,124	4,303,452	3,303,967	1,283,771	851,343
Weapon_AK74su_Rifle	1,689,061	1,531,108	972,586	869,760	583,209	541,945	133,266	119,403
Weapon_Vintorez_	25.064	29.001	22.220	16 147	10.222	0.000	2 (11	2.046
Sniper Weapon Guerilla	35,064	28,091	22,230	16,147	10,223	9,898	2,611	2,046
RPG7_Rocket	78,110	72,804	51,695	48,906	23,206	21,193	3,209	2,705
Weapon_M2_HMG	47,365	29,322	18,933	11,934	17,663	9,573	10,769	7,815
Weapon_AT4_Rocket	3,574	3,897	1,315	1,714	1,338	1,476	921	707
Weapon_SPR_Sniper	122,247	110,350	69,786	63,259	51,620	46,628	841	463
Weapon_M9_Pistol	55,208	54,868	27,807	28,727	23,472	23,192	3,929	2,949
Weapon RPG7 Rocket	624	180	260	63	237	70	127	47
Weapon M24 Sniper	88,990	69,854	48,226	38,058	39,164	30,469	1,600	1,327
Weapon_MosinNagant_			,	,		20,103	-,	-,
Sniper	2,248	1,398	1,228	723	914	583	106	92
Weapon_M82_Sniper	70,024	55,529	51,624	40,726	17,682	14,154	718	649
Throw_M14_Incendiary	3,828	2,706	2,319	1,761	1,053	686	456	259
Weapon_M870_Shotgun	306	254	0	0	6	5	300	249
Weapon_SVD_Sniper	2,299	1,304	1,256	551	760	545	283	208
Throw_MILES_Grenade	17,460	13,402	7,635	5,610	7,349	6,035	2,476	1,757
Throw_RGD5_Frag	5	5	2	1	2	1	1	3
	36,987,769	29,273,497	18,231,610	14,293,594	13,864,854	11,323,039	4,891,305	3,656,864

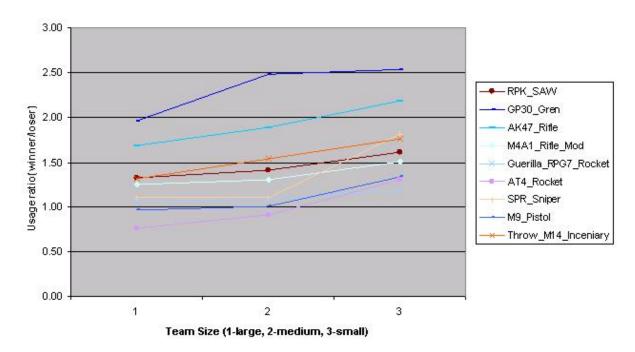
Table 16 The ratios of how many times each type of weapon has been used for Winner and Loser teams for large (more than 8), medium (between 4 and 9), and small (less than 5) size teams

	Tsize>8	9>Tsize>4	TSize<5
Weapon name	Winner/Loser	Winner/Loser	Winner/Loser
Weapon_M203_Gren	1.27	1.14	1.29
Weapon_M249_SAW	1.25	1.10	1.22
Weapon_M16A2_Rifle	1.41	1.30	1.40
Throw_M84_Stun	1.29	1.26	1.25
Throw_M67_Frag	1.27	1.23	1.18
Weapon_RPK_SAW	1.33	1.41	1.61
Throw_M83_Smoke	1.06	1.10	1.07
Weapon_GP30_Gren	1.96	2.48	2.53
Weapon_AK47_Rifle	1.68	1.89	2.18
Weapon_M4A1_Rifle_Mod	1.25	1.30	1.51
Weapon_AK74su_Rifle	1.12	1.08	1.12
Weapon_Vintorez_Sniper	1.38	1.03	1.28
Weapon_Guerilla_RPG7_Rocket	1.06	1.09	1.19
Weapon_M2_HMG	1.59	1.85	1.38
Weapon_AT4_Rocket	0.77	0.91	1.30
Weapon_SPR_Sniper	1.10	1.11	1.82
Weapon_M9_Pistol	0.97	1.01	1.33
Weapon_RPG7_Rocket	4.13	3.39	2.70
Weapon_M24_Sniper	1.27	1.29	1.21
Weapon_MosinNagant_Sniper	1.70	1.57	1.15
Weapon_M82_Sniper	1.27	1.25	1.11
Throw_M14_Incendiary	1.32	1.53	1.76
Weapon_M870_Shotgun		1.20	1.20
Weapon_SVD_Sniper	2.28	1.39	1.36
Throw_MILES_Grenade	1.36	1.22	1.41
Throw_RGD5_Frag	2.00	2.00	0.33
Total	1.28	1.22	1.34

We also investigated the use of particular weapons in particular missions, irrespective of the team size. First we calculated the number of times a weapon was used for a specific mission. As different missions were played by different number of players, this data was normalized by dividing by the number of players on each team. As a result, Table 17 presents the ratios of the number of time a weapon has been used for a particular mission by winning teams to the number of time a weapon has been used for a particular mission by losing teams.

The first observation is that the winners always use weapons more frequently than the losers. This means that the frequent use of weapons increases chances to win the game regardless the size of the team. Another observation is that there are two equally sized groups of missions. One group includes those who have the ratios of winner/loser weapon use higher for the small teams (Figure 29), and so for whom it is more crucial to use weapons if the team is small. The other group includes those who have the ratios higher for the large teams (Figure 30), and so for whom the use of the weapon influences the game outcome stronger if the team is large.

Figure 27 Weapon Usage ratio (Winner/Loser) vs. Team Size for different WEAPON, Weapon choice affects SMALL SIZE teams



Figure~28~We apon~Usage~ratio~(Winner/Loser)~vs.~Team~Size~for~different~WEAPON~,~We apon~choice~affects~LARGE~SIZE~teams

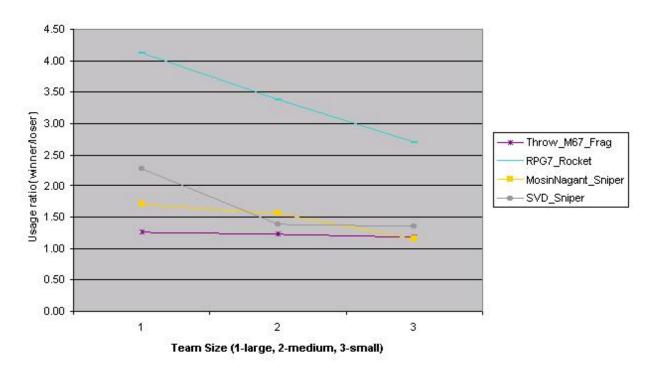


Table 17 The ratios of how many times "per player" a weapon has been used for Winner and Loser teams for large (more than 8), medium (between 4 and 9), and small (less than 5) size teams for different missions.

Mission	All	Team size>8	9>TeamSize>4	Team size<5
	Winner/Loser	Winner/Loser	Winner/Loser	Winner/Loser
Pipeline	1.36	1.33	1.40	1.46
Pipeline_SF	1.38	1.35	1.41	1.46
SFvillage	1.52	1.51	1.54	1.51
SFArctic	1.60	1.56	1.75	1.44
MOUT_McKenna	1.39	1.38	1.38	1.42
Sfhospital	1.24	1.21	1.26	1.39
Bridge	1.60	1.72	1.57	1.43
Bridge_SE	1.59	1.67	1.58	1.43
Insurgent_Camp	1.45	1.46	1.44	1.40
Weapons_Cache	1.43	1.38	1.45	1.47
Weapons_Cache_SE	1.44	1.40	1.46	1.54
SFrecon	1.69	1.80	1.66	1.64
SFcsar	1.47	1.44	1.52	1.56
SFsandstorm	1.37	1.35	1.40	1.43
HQ_Raid	1.65	1.69	1.67	1.57
Radio_Tower	1.61	1.66	1.59	1.29
River_Basin	1.62	1.60	1.68	1.46
Mountain_Pass	1.62	1.67	1.61	1.38
Mountain_Pass_SE	1.69	1.74	1.70	1.46
Montain_Ambush	1.36	1.31	1.39	1.55
Tunnel	1.42		1.40	1.48
Swamp_Raid	1.36	1.18	1.39	1.36
FLS	0.86	1.57	1.34	1.27
JRTC_Farm	1.46		1.55	1.30
Total	1.39	1.40	1.37	1.39

Figure 29 Weapon Usage ratio (Winner/Loser) vs. Team Size for different MISSIONS, Weapon choice affects SMALL SIZE teams

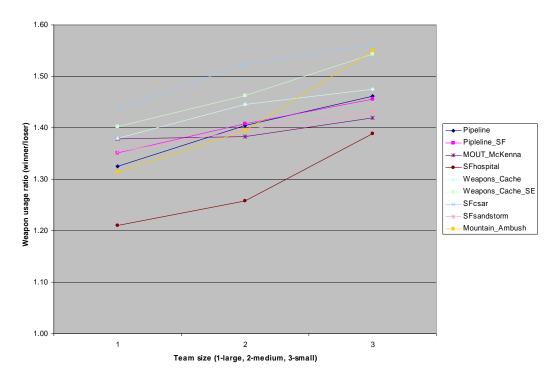


Figure 30 Weapon Usage ratio (Winner/Loser) vs. Team Size for different MISSIONS, Weapon choice affects LARGE SIZE teams

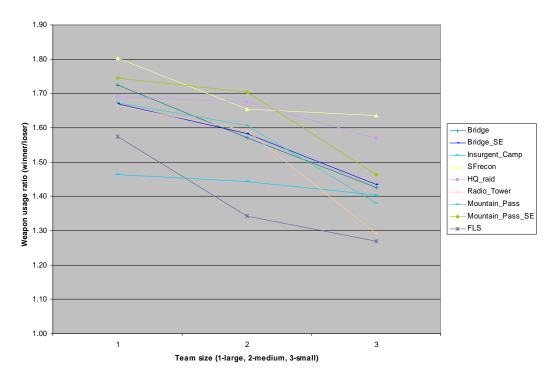


Table 18 The damage caused by the players from winning and losing teams for large (more than 8), medium (between 4 and 9), and small (less than 5) size teams for different missions.

Mission	Damage Amount								
	Winner Te	eam			Loser Team				Winner/
	Average	StdDev	Max	Min	Average	StdDev	Max	Min	Loser
Pipeline	13.38	21.13	100	0	11.50	19.63	100	0	1.16
Pipeline_SF	13.79	20.22	100	0	11.78	18.82	100	0	1.17
SFvillage	14.23	21.95	100	0	12.06	20.46	100	0	1.18
SFArctic	15.93	22.77	100	0	12.56	20.99	100	0	1.27
MOUT_McKenna	16.22	21.74	100	0	15.03	21.00	100	0	1.08
Sfhospital	14.34	22.48	100	0	13.76	22.19	100	0	1.04
Bridge	14.03	25.10	100	0	10.19	22.14	100	0	1.38
Bridge_SE	13.93	24.80	100	0	9.64	21.41	100	0	1.45
Insurgent_Camp	14.28	24.40	100	0	11.62	22.09	100	0	1.23
Weapons_Cache	14.98	23.18	100	0	12.98	21.99	100	0	1.15
Weapons_Cache_SE	14.02	22.03	100	0	12.18	20.59	100	0	1.15
SFrecon	13.61	21.16	100	0	9.72	18.66	100	0	1.40
SFcsar	13.75	21.62	100	0	11.77	20.40	100	0	1.17
SFsandstorm	14.85	20.22	100	0	14.28	19.44	100	0	1.04
HQ_Raid	19.76	16.60	100	0	17.51	16.42	100	0	1.13
Radio_Tower	13.76	24.29	100	0	10.56	21.70	100	0	1.30
River_Basin	19.11	20.00	100	0	16.66	19.66	100	0	1.15
Mountain_Pass	14.76	25.70	100	0	10.32	21.97	100	0	1.43
Mountain_Pass_SE	13.13	23.69	100	0	10.20	21.36	100	0	1.29
Montain_Ambush	15.15	23.53	100	1	12.79	21.56	100	1	1.18
Tunnel	16.22	17.75	100	0	14.66	16.40	100	0	1.11
Swamp_Raid	30.26	26.18	100	1	29.65	24.32	100	1	1.02
FLS	11.88	19.31	100	1	8.53	16.29	100	1	1.39
JRTC_Farm	14.28	19.94	100	0	10.85	17.02	100	1	1.32

5.3.3 Damage results analysis

Use of a weapon causes damage if the target is hit. The damage is recorded as a string describing the location of the damage (head, neck, leg etc) and an integer number (between 0 and 100) for the severity of the damage. This section focuses on the quantitative damage results. Table 18 presents the average damage (per event) caused by winning and losing teams for different missions. These average values measure of precision of the weapon use: the high values correspond to serious wounds in places like head or neck, the low values correspond to wounds of arms or legs. The results show that the winning teams on average hit targets more precisely causing more damage to the opponent, which increases the chances of winning the game. The greatest impact of the precision is found for the Bridge_SE and Mountain_Pass missions (the ratios are 1.45 and 1.43, respectively). The missions which are least affected are Swamp_Raid and SFhospital missions (the ratios are 1.02 and 1.04, respectively). The standard deviation for the average damage score is quite high, exceeding the average values.

5.3.4 Communication usage analysis

Communication is performed through radio or voice broadcast. These two types of the broadcast differ in the radius it can reach the listeners. Although theoretically some messages can not be heard by all team players, we make a reasonable assumption that each communication message is heard by all team members. The precise receivers of each communication could not be determined by the data available. The meaning of the message might not directly be related to the actions and carry "irrelevant" information (for example, "hi all"). For this data analysis we do not distinguish between relevant and irrelevant messages and count them all. The filtering of relevant information is left for future work. Table 19 presents the number of times communication messages have been used by the winning and losing teams of different size for different missions. One result from the table is that in average the winning teams use more communication messages than the losing teams.

Table 19 The number of times a communication message has been used for winning and losing teams for large (more than 8), medium (between 4 and 9), and small (less than 5) size teams for different missions.

Mission	All teams		Team size>8	3	9>TeamSiz	e>4	Team size<	< 5
	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser
	Team	Team	Team	Team	Team	Team	Team	Team
Pipeline	594,090	408,732	372,721	256,870	176,467	120,690	44,902	31,172
Pipeline_SF	382,987	261,046	201,614	135,243	144,671	98,457	36,702	27,346
SFvillage	172,535	119,155	71,117	50,741	85,160	56,159	16,258	12,255
SFArctic	180,687	145,703	89,353	73,651	68,662	55,380	22,672	16,672
MOUT_McKenna	315,809	233,105	86,388	62,000	161,745	122,041	67,676	49,064
SFhospital	651,216	508,968	333,883	259,683	259,749	202,664	57,584	46,621
Bridge	585,609	450,900	254,412	197,194	237,687	181,709	93,510	71,997
Bridge_SE	137,759	100,423	72,370	52,266	40,884	30,994	24,505	17,163
Insurgent_Camp	431,610	304,843	236,387	170,113	153,711	105,209	41,512	29,521
Weapons_Cache	378,718	273,436	105,058	75,915	216,315	153,997	57,345	43,524
Weapons_Cache								
_SE	150,766	108,557	94,230	69,449	40,927	27,852	15,609	11,256
SFrecon	16,930	12,313	4,652	3,018	8,817	6,396	3,461	2,899
SFcsar	202,940	139,998	135,859	93,629	55,596	38,279	11,485	8,090
SFsandstorm	111,139	75,934	73,581	49,343	30,025	20,547	7,533	6,044
HQ_Raid	18,005	12,691	1,878	1,313	12,031	8,486	4,096	2,892
Radio_Tower	62,444	45,056	47,047	34,981	11,446	7,804	3,951	2,271
River_Basin	35,765	23,254	10,275	6,731	20,540	12,551	4,950	3,972
Mountain_Pass	80,542	58,411	50,496	35,672	21,604	16,416	8,442	6,323
Mountain_Pass								
_SE	43,924	31,871	28,833	21,124	9,916	7,028	5,175	3,719
Montain_	40,993	30,822	26,436	19,436	11,021	8,615	3,536	2,771
Ambush Tunnel	40,993	27,512	20,430	19,430	27,230	18,338	14,081	9,174
	14,503	9,781	1,580	1,010	8,310	5,575	4,613	3,174
Swamp_Raid FLS	68,750	48,008	43,956	22,413	16,924	17,691	7,870	7,904
JRTC Farm	7,745	6,186	43,930	22,413	5,217	4,092	2,528	2,094
Total	4,726,777	3,436,705	2,342,126	1,691,795	1,824,655	1,326,970	559,996	417,940

Table 20 The ratios of how many times per player a communication message has been used for winning and losing teams for large (more than 8), medium (between 4 and 9), and small (less than 5) size teams for different missions.

Mission	Team size>8	9>TeamSize>4	Team size<5
	Winning/Losing	Winning/Losing	Winning/Losing
Pipeline	1.66	1.71	1.62
Pipeline_SF	1.68	1.65	1.53
SFvillage	1.69	1.79	1.51
SFArctic	1.59	1.61	1.55
MOUT_McKenna	1.43	1.51	1.49
Sfhospital	1.35	1.38	1.34
Bridge	1.72	1.63	1.45
Bridge_SE	1.82	1.64	1.66
Insurgent_Camp	1.59	1.62	1.55
Weapons_Cache	1.58	1.57	1.49
Weapons_Cache_SE	1.59	1.70	1.51
SFrecon	1.98	1.65	1.53
SFcsar	1.62	1.67	1.64
SFsandstorm	1.58	1.65	1.42
HQ_Raid	1.60	1.58	1.57
Radio_Tower	1.78	1.85	2.02
River_Basin	1.86	1.87	1.51
Mountain_Pass	1.64	1.55	1.55
Mountain_Pass_SE	1.87	1.88	1.82
Montain_Ambush	1.47	1.55	1.50
Tunnel		1.60	1.63
Swamp_Raid	1.54	1.69	1.56
FLS	1.05	1.88	1.59
JRTC_Farm		1.46	1.40
Total	1.55	1.57	1.50

The per-team communication scores were normalized by dividing by the number of players on the team. The results are presented in Table 20. Unlike the weapon usage, there is only a one type of group, which has higher winning/loser ratios for the large teams than for the small teams. This group is small and consists of four missions only (Figure 31). This observation shows that in general the communication between players affects the game outcome in roughly the same degree for any team size.

According to table 21, winners and losers show significant differences in the usage of the Report-In communications. First of all, winning teams communicate more frequently with Report-In messages than losing teams. Also, there are slight differences among teams according to the size. In figure 32, the fact that the medium sized teams communicate most frequently is quite unexpected. The small teams show the lowest Report-In frequency, and the Report-In frequency of the large teams is in the middle between the frequency of the small team and the frequency of the medium team.

Figure 31 Communication Usage ratio (Winning/Losing) vs. Team Size for different MISSIONS, Weapon choice affects LARGE SIZE teams

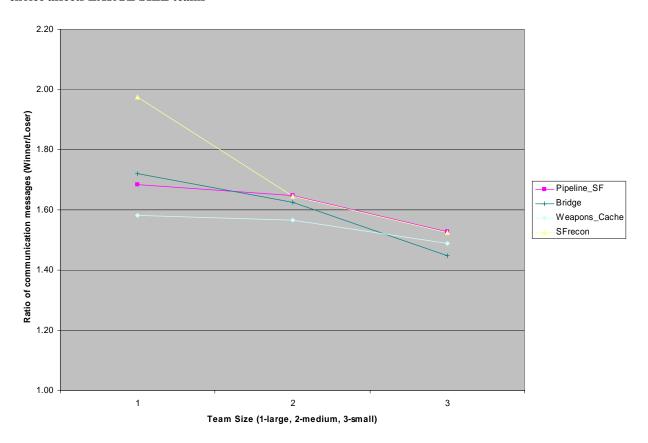


Table 21 Average frequency of the Report-In Communication for the first period, the second period, the third period, and the entire game

	First Period	Second Period	Third Period	Total
Winner	0.334436	0.422924	0.403572	1.160932
Winner (Small)	0.283679	0.368074	0.343498	0.995251
Winner				
(Medium)	0.376919	0.473182	0.452769	2.156183
Winner (Large)	0.331137	0.415463	0.40064	1.14724
Loser	0.272252	0.248579	0.119347	0.640178
Loser (Small)	0.222244	0.236698	0.110972	0.569914
Loser				
(Medium)	0.303073	0.259198	0.118222	0.680493
Loser (Large)	0.281725	0.247854	0.126611	0.65619

Medium

Large

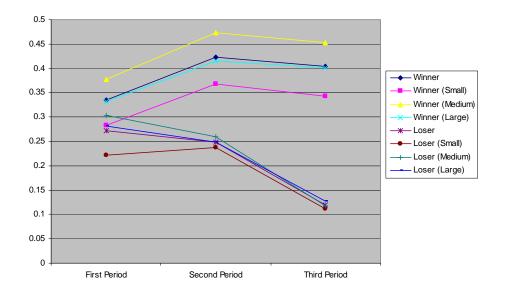
Figure 32 Different Report-In Communication Usages between Winners and Losers through the Entire Game

Figure 33 suggests that winning teams tend to communicate more frequently in the middle of the game. On the other hand, the frequency of the Report-In communication of losers keeps decreasing as game progresses. A particularly noticeable decline occurs for losing teams between the second and third periods, due to losing their players towards the end. Even though winners show slight decrement in the Report-In communication during that period, the decrement of the winner is very tiny when it is compared to the decrement of the loser.

Small

All Size

Figure 33 Different Report-In Communication Usages according to the Team Size and the Periods of the Games



5.3.4 Communication network analysis using ORA

5.3.4.1 Correlation analysis between team performance measures and team organizational measures

This section examines correlations between team performance measures and team organizational measures. The list of the measures and indexes can be found at the Appendix B of this report. The set of team organizational measures includes three types of measures:

- general statistical measures
- ORA node-level measures
- ORA network level-measures (For two communication networks: Report-In communication and Normal communication)

The team performance variables are six variables which represent team performance and the game result, as reported in the log files:

- the number of survived players
- the average number of survived players
- the number of killed opponent players
- the average number of killed opponent players
- the players' aggregated total scores
- the average of the players' aggregated total scores
- the average of new score

Sample games were divided into 8 categories according to the team size to allow for separate analysis. The following categories were used:

- Winning Teams (All the winners without considering the team size)
- Winning Teams (Small teams: team size < 5)
- Winning Teams (Medium teams: 4 < team size < 9)
- Winning Teams (Large teams: team size > 8)
- Losing Teams (All the winners without considering the team size)
- Losing Teams (Small teams: team size < 5)
- Losing Teams (Medium teams: 4 < team size < 9)
- Losing Teams (Large teams: team size > 8)

Correlations were run between all measures. The correlation analyses were done between those six indices and the general statistics and the ORA results (436 measures, the list of the measures is in the appendix B) The 20 most highly correlated measures by absolute value are listed from table C-1 to table C-14 in Appendix C.

In many cases, the correlation values of the large team category are higher than those of the small team category. Additionally, among the top 20 correlation factors of the large teams, we

can see more organizational factors are listed than in the other category lists. The reason is that if a team is small, there will be fewer communications between team members and their communication network will contain less information. On the other hand, for large teams, the organizational measures tend to have higher correlation with team performance measures.

In table C-1 and table C-2, there are several measures which are related to the number of the surviving players. Longer combat time, more shots in the first part of the game, and more frequent normal communication negatively affect team members' survival. Clearly the survival ratio would be lower in longer games because there are more opportunities for the players to get killed. The data show that a high amount of weapon fire events in the first part of the game increases the rate of death across the entire game. This could mean that if two teams are eager to fight against each other from the beginning, both of them will have more casualties and that, if both sides are reluctant to open fire from the start of the game, both teams will have fewer casualties.

Also, many general statistics related to the number of the normal communications are listed in table C-1 and C-2. These measures have a negative correlation with team members' survival. One might be surprised that normal communication does not help team members' survival, because they are intentionally transmitted communication messages and presumed to be helpful for the teams. However, if the contents of the normal communication are just chatting and not related to the combat, the communication will distract team members from the dynamically changing combat situation. Tables C-3 and C-4 list the average number of survivals (number of survivals / number of team members). The explanations of tables C-1 and C-2 can be equally applied to tables C-3 and C-4.

Tables C-9, C-10, C-11 and C-12 display the top 20 correlation between the aggregated team members' total score or the average of the aggregated team members' total score and various measures. These tables showed relatively low correlations; many were below 0.2.

Table C-13 and C-14 illustrates the 20 highest correlation between the aggregated new score and various measures. Among variables, weak component count has high minus correlation with new score, which means that the team will have better new score if it has less weak component in the communication network. Also, the diameter of the communication network does negative impact on the new score, so the correlation analysis reveals that the more centered and web shaped team will better perform in the perspective of new score.

5.3.4.2 Regression analyses between organizational measures and amount of damage received and inflicted

We conducted regression analyses comparing the Report-In who-talked-after-whom network measures with various team level performance measures: average total score, average objective score, average kill score, team received damage, team inflicted damage, and so on. Though using all 436 measures might improve the result of the regression, only ORA network measures were selected to keep the model simpler. For the regression analysis, about 95300 teams were sampled from the dataset, and all of them had more 10 or team members. This restriction made sure that there was sufficient information in the communication network for the analysis to be interesting. Among the team level regression results, two regression models show fairly good adjusted R-

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square values and are listed in table 22. Additionally, this means that the ORA measures are quite useful information to predict the amount of damage team will inflict/receive.

Table 22 Adjusted R-square from regression analysis between ORA network level measures and team received/inflicted damage

Explanatory variable	Dependent variable	Adjusted R value
Report-In Who-talked-after- whom network ORA analysis	Aggregated Team Received Damage	0.889
network level measures	Aggregated Team Inflicted Damage	0.9238

The amount of received damage is surprisingly closely correlated with the number of casualties during the game. Since number of casualty varies very little, we did not use it in the regression analyses, and instead we chose team received damage as a team performance measure. According to Table 23, adjusted R-square is relatively good at 0.889. Figure 34 illustrates that predicted values are fairly near to the actual values. The regression analysis can predict reasonably well the amount of damage the team will receive by utilizing the ORA network level measures.

As in the previous regression analysis, the amount of inflicted damage was chosen instead of the number of enemies killed, because they are closely correlated to each other, and the number of enemies killed varies very little across the dataset. Table 24 shows that the adjusted R-square value is very good at 0.9238. Figure 35 does not show any significant outliers, and the data points are well distributed near the regression line. We conclude that the amount of damage the team will inflict on the enemy is well explained by using the regression model made by the ORA network level measures. The coefficients calculated by the two regression analyses can be found in Appendix D.

Figure 34 Predicted value X Actual value scatter plot generated by regression analysis between ORA network level measures and team received damage

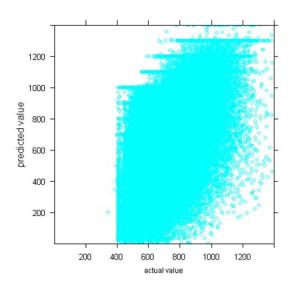


Table 23 Regression analysis result summary, ORA network level measures vs team received damage

RSquare	0.889
RSquare Adj	0.889
Residual standard error	263.9
Observations (or Sum Wgts)	95322

Figure 35 Predicted value X Actual value scatter plot generated by regression analysis between ORA network level measures and team inflicted damage

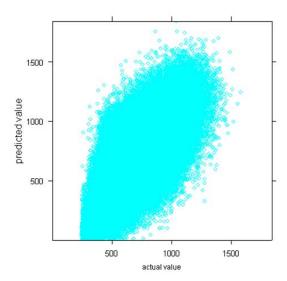


Table 24 Regression analysis result summary, ORA network level measures vs team inflicted damage

RSquare	0.470707
RSquare Adj	0.4705906
Root Mean Square Error	214.34967
Mean of Response	659.8725
Observations (or Sum	
Wgts)	95529

5.3.5 Analysis of top 1000 teams and finding alternative strategies to win

We used the regression results from as a new measure of team performance. The top 1000 teams were identified using this measure, and analyzed to find the different strategies teams use to win. The various measures of a team, general statistics, ORA network level measures, and aggregated ORA node level measures are one way of describing the strategies employed by the teams. A team who has an unusual "profile" among the top 1000 teams on the features used in the regression represents a team with uncommon strategies which nevertheless achieved top 1000 team status.

The teams were grouped into 3 categories for each measure in order to reduce the noise in the measures. The formula in figure 36 describes the grouping method. Although this method

reduces the variance of the data, it makes understanding and interpreting the following analyses easier.

Figure 36 Formula for labeling measures into groups

For measure A, let $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ If actual data is a, $(beta) = \begin{pmatrix} 3', & \text{when} & a \ge m + \frac{1}{2}d \\ 2', & \text{when} & m - \frac{1}{2}d \le a < m + \frac{1}{2}d \\ 1', & \text{when} & a < m - \frac{1}{2}d \end{pmatrix}$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ A) = m, (standard \ deviation \ of \ A) = d$ (the labeled data for a) $(average \ of \ average \ of \ average$

5.3.5.1 Principal Component Analyses on entire measures

A principal component analysis was done to convert the measures into the smaller number of variables, to make it simpler to recognize the variance among the top 1000 teams. We also used k-means clustering to group the 1000 teams into 10 clusters. Table 25 shows 10 clusters determined by using k-means analysis on top 1000 teams

Table 25 Clusters determined by kmeans analysis on top 1000 teams

Cluster	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9	Cluster10
# of Teams	173	41	97	108	215	58	41	6	65	196

The top 36 principal components captured over 95% of the variance, and 67.5% variance was captured using only 3 principal components. The summary of the principal component analysis can be found in Appendix E.

Figure 37 shows a scatter-plot of the top 3 principal components of the regression, grouped by color into 10 groups. The orange cluster, number 4, is noticeably separate from the other groups. The pink, cyan, and magenta, number 9, number 8, number 7 respectively, together form another outlying group.

Figure 37 Scatter plot with 3 most important principal components explaining 67.5% of variance

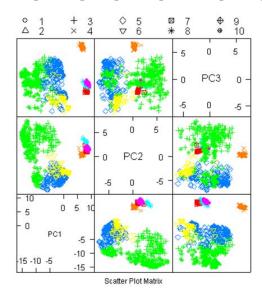
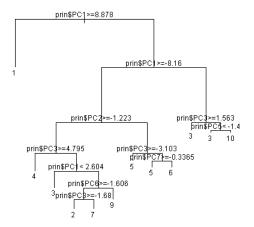


Figure 38 Decision tree showing how clusters can be divided by using principal components



While the principal component analysis cluster 4 is an outlying cluster, it is still hard to say what unique characteristics make cluster 4 stand out. Therefore, information gain for each variable was calculated to determine what most distinguished cluster 4 from the other clusters. Figure 39, shows the 5 measures with the most information gain separating cluster 4 from the other clusters. It seems that the teams in cluster 4 have relatively low resource load, resource exclusivity and high number player, number soldier, weak component members.

12 Low ■ Medium High 0.8 0.6 0.2 0 The other The othe Selected The other Selected The other Selected Selected The othe Cluster clusters Cluster clusters resourceload avg_resourceexclusivity numplayer numsoldier avg_w eakcomponentmembers

Figure 39 Frequency percentage of labeled measures with top 5 information gain (Selected cluster is cluster 4, and the other clusters are the rest of the clusters.)

5.3.5.2 Correspondence Analysis on entire measures and ORA network measures

In this section we present a correspondence analysis on the measures of the top 1000 teams. The correspondence analysis maps all 436 measures into a two-dimensional plane, allowing one to view the distribution of measures and clusters at the same time, so that their relationship and correlation will be visible.

Figure 40 shows a correspondence analysis across the 10 clusters and 436 measures. As in the principal component analysis, cluster 4 cluster 4 is the most outlying cluster, but it also cluster 2, 5, and 9 are away from the cluster 1, 3, 6, 7, 8, and 10. By observing the measures around the cluster 4, a unique attribute of cluster 4 can be found, which is a medium level of agentlevel_max_agent socio economic power.

Figure 41 show a correspondence analysis of the clusters the ORA 31 network level measures. Still, cluster 1, 3, 6, 7, 8, and 10 are close to each other, and the other clusters are scattered across the graph. The major aspects of clusters 1, 3, 6, 7, 8, and 10 are medium or high diameter, high strong component count, high interdependence, and so on. Cluster 4 and 5 are somewhat closely located on the graph, and their similarities in terms of ORA network measures are high span of control, medium interdependence, and medium average speed,. Cluster 9 and cluster 2 are far from all of the ORA measures, meaning those clusters do not show strong relationships to those measures.

Figure 40 Graph from correspondence analysis, with 439 measures and 10 clusters

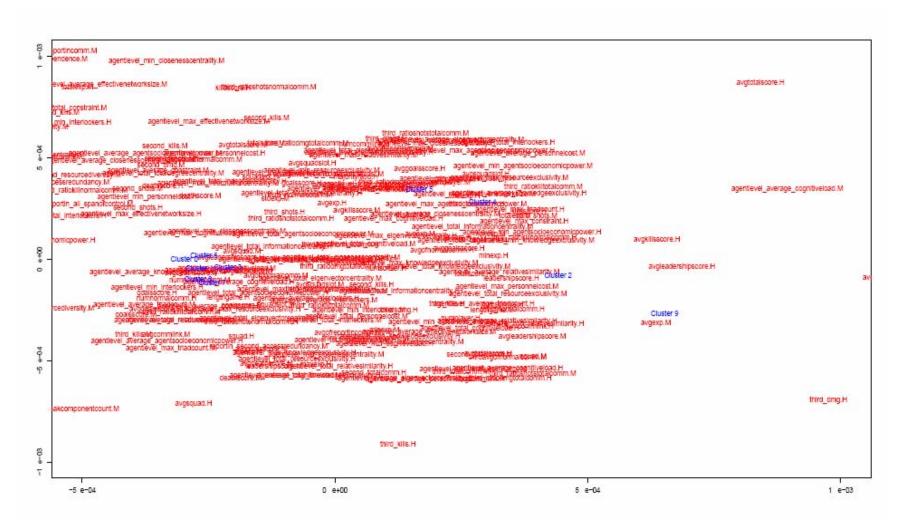
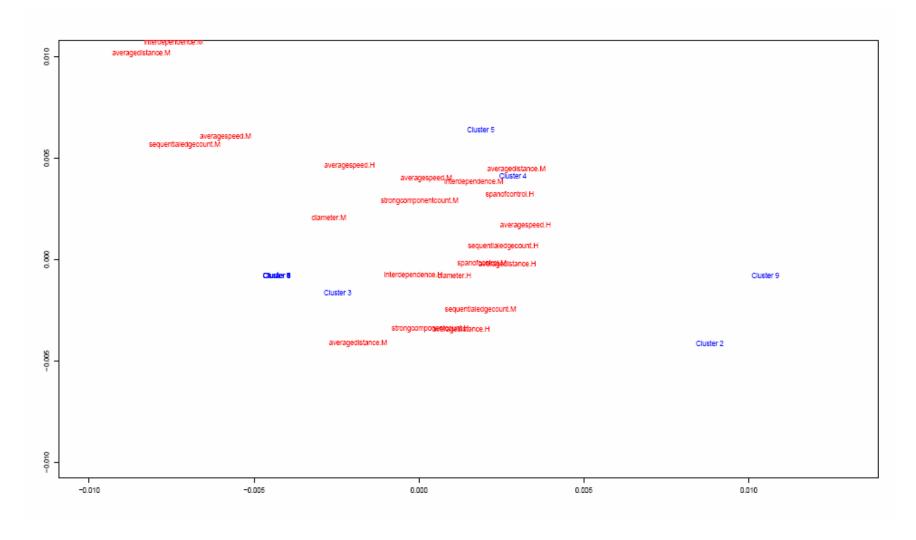
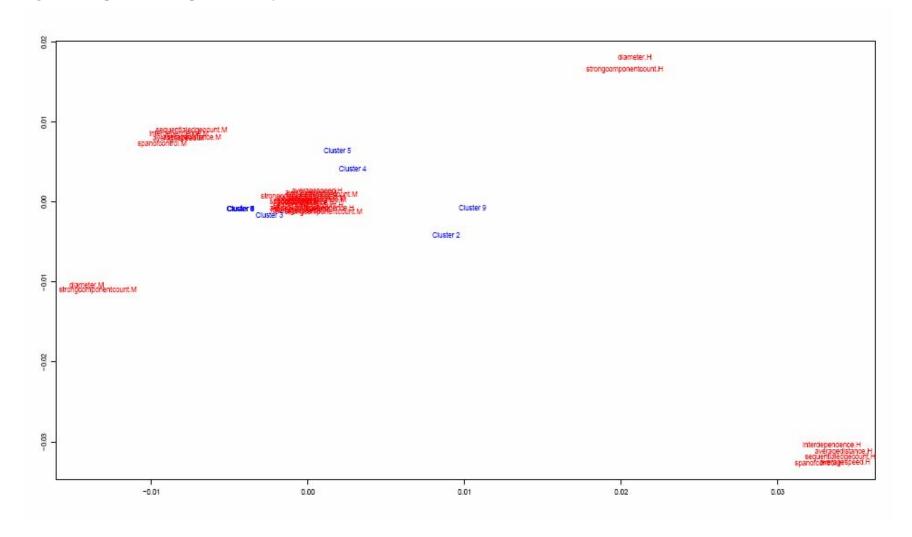


Figure 41 Graph from correspondence analysis, with 31 ORA measures and 10 clusters, narrow scoped with focusing the distribution of clusters and with some usage of jittering function







5.4 Clan level data analysis

5.4.1 Overall clan level statistics and interpretation

Clans are informal groupings of players created under their own initiative. A clan may have just a few players, or it could have hundreds. Clan members form teams when playing other players or clans. Typically clan members create screen names that incorporate the name of their clan. For example, followings are the player names with the clan names (clan names are separated by brackets):

[ROM] E.T., [HF]TONIC, [HF]SARYIO, [LLJK]RALLY VINCENT, [HA]LITTLEBLUEDOG, {PAF}CLONE-K, [WOLF]CHUCKELS, [COFR]MUTHAPLUCKA, -XXX-WAFFENFOCK, [HEL]REAPER, [SES] OCEAN, [75TH]SOLAR, [75TH]SGT.CREATE, [JAPS]SUICIDE, [SA]SWORDFISH, [BBB]CASHMAN, [75TH]SNIPERKILLER

A customized parsing program was used to pick up the clan names out of the entire player name. This information was used to calculate two measures: clanishness-strong and the clanishness-weak. Clannishness-strong represents the percentage of players on a team that are on the most common clan in that team (a team could have players from multiple clans). Clannishness-weak the ratio of clan members from any clan on a team. For instance, if a team of five players has three players from clan SES, and one member from clan 75th, the clanishness-strong ratio for the team is 0.6 (3/5), and the clanishness-weak is 0.8 (4/5).

Figure 43 shows that on average between 1 and 2 distinct clans are represented on all teams. There are some outlying teams which have more than two same clan members in the data set.

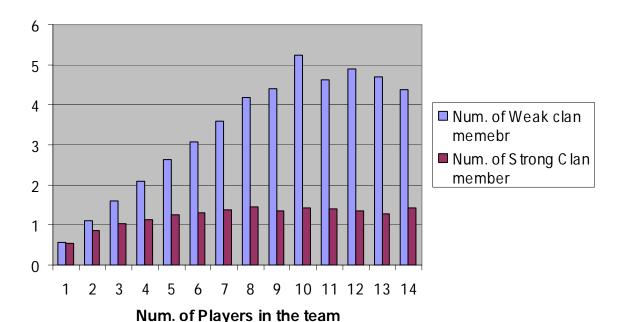


Figure 43 The number of clan members in the teams

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5.4.2 Clanishness-strong statistics and interpretation

Figure 44 shows a histogram of clannishness-strong of the sampled teams. It shows that most teams have one or more clan involved team members and only 50,000 teams are composed purely of non-clan members. In addition, approximately 30,000 of teams are composed only of players of the same clan.

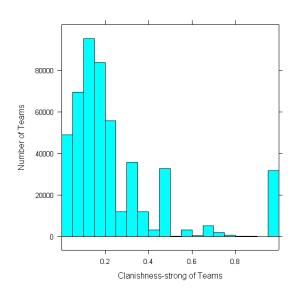


Figure 44 the number of teams according to the clannishness-strong

Next the teams were divided into three groups: a high clannishness-strong group, a middle clannishness-strong group, and a low clannishness-strong group. The high clannishness-strong group consists of teams that have more than 0.66 clannishness-strong values, middle clannishness-strong teams have a value between 0.33 and 0.66, and the remaining teams are classified as the low clannishness-strong group. The number of teams in the high clannishness-strong group is far smaller than the sample number of the low clannishness-strong group, but all the three groups represent a fairly large sample of the overall population. The detailed sample numbers for the groups are listed in Table 26.

Figures 45 and 46 show the winning and losing rates of the three groups. The winning rate of the high clannishness-strong group is 8% higher than its losing rate, while the winning rate of the low majority group is slightly lower than its losing rate, indicating that high clannishness teams are much more effective, presumably due to self selection of better players and increased experience and team work as the clans play more and more games together. The average survival rate shows a similar pattern across groups. The high clannishness-strong group has approximately 10% greater chance to survive than the low clannishness-strong group.

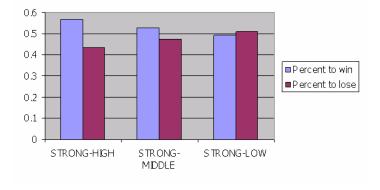
Table 26 Dividing sample teams into three groups according to the clannishness-strong: $1 \ge high$ clannishness-strong ≥ 0.66 , $0.66 \ge hiddle$ clannishness-strong ≥ 0.33 , $0.33 \ge high > 0.33 \ge h$

Category	Number of Teams
High clanishness-strong	13400
High clanishness-strong (Winner) High clanishness-strong (Loser)	7584 5816
Middle clanishness-strong	87029
Middle clanishness-strong (Winner) Middle clanishness-strong (Loser)	45858 41171
Low clanishness-strong	343974
Low clanishness-strong (Winner)	169040
Low clanishness-strong (Loser)	174934

Figure 47 shows the average level of report-in and regular communication across the groups. As with winning teams generally, the high clannishness group relies more on report-in and less on regular communication than do the other groups. The teams in the high clannishness-strong group often communicate through Report-In communications, not Normal communications like Team-Say and Whisper. On the other hands, the teams classified as the low clannishness-strong group have a higher Normal communication frequency compared to the rate of the high clannishness-strong group.

The low clannishness groups also have a higher overall level of regular communication, meaning that members of the low clannishness-strong grouped team wanted to use natural language as a communication method instead of the report-in, which only reports location using a hot-key. Report-in is not only much faster to execute than regular communication, but may convey the most relevant information to help the team win (player location).

Figure 45 Winning rates and losing rates across the three groups in the clannishness-strong

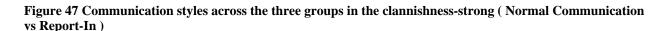


0.5 0.45 0.4 0.35 0.3 0.25 0.2

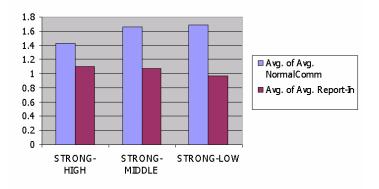
STRONG-

MIDDLE

Figure 46 Average player survival ratio across the three groups in the clannishness-strong



STRONG-LOW



5.4.3 Clanishness-weak statistics and interpretation

0.15 0.1 0.05 0

STRONG-HIGH

Figure 48 shows the distribution of clannishness-weak across teams. It shows generally a normal distribution, but with two significant spikes a 0.0 and 1.0. Most teams have a clannishness-weak value between 0.2 and 0.8.

In table 27 the teams are divided into three groups according to the clannishness-weak values. When compared to the division of the clannishness-strong, the three groups of the clannishness-weak shows more evenly distributed sample numbers across the groups. The criterion for the grouping is same as with clannishness-strong.

The tendencies observed in the clannishness-strong are also shown in the clannishness-weak. The high clannishness-weak group shows higher winning rate, higher survival rate, and higher Report-In communication rate than the middle and low clannishness-weak groups do. However, there are two differences between the high clannishness-strong group and the high clannishness-weak group.

0.2

Figure 48 The number of teams according to the clannishness-weak

20000

First, while the high clannishness-strong group does not use many Normal communications frequently, the high clanishness-weak group uses the Normal communication as almost same as the middle clanishness-weak group and the low clanishness-weak group. It can be concluded that the high clanishness-strong team members do not need to communicate with the normal message: they use communication just to broadcast their locations. However, the high clanishness-weak team members send more normal text messages to the other team members, possibly because they are not as familiar with the play style of players from other clans.

0.4

nв

Clanishness-weak of Teams

0.8

Second, the survival rate of the high clanishness-strong group is approximately 5% higher than the survial rate of the high clanishness-weak group. Both of these results suggest composing a team with players from a single clan increases performance.

Table 27 Dividing sample teams into three groups according to the clannishness-weak: $1 \ge high$ clannishness-weak ≥ 0.66 , $0.66 \ge high$ clannishness-weak ≥ 0.33 , $0.33 \ge high$ clannishness-weak ≥ 0

Category	Number of Teams
High clanishness-weak	138960
High clanishness-weak (Winner)	75857
High clanishness-weak (Loser)	63103
Middle clanishness-weak	211889
Middle clanishness-weak (Winner)	105336
Middle clanishness-weak (Loser)	106553
Low clanishness-weak	93554
Low clanishness-weak (Winner)	41289
Low clanishness-weak (Loser)	52265

Figure 49 Winning rates and losing rates across the three groups in the clannishness-weak

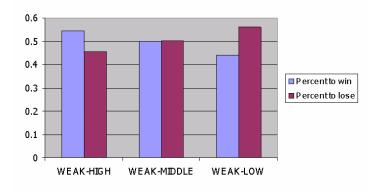


Figure 50 Average player survival ratio across the three groups in the clannishness-weak

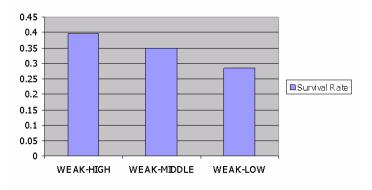
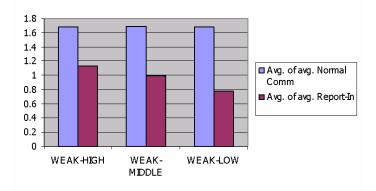


Figure 51 Communication styles across the three groups in the clannishness-weak (Normal Communication vs Report-In) $\frac{1}{2} \left(\frac{1}{2} \right) = \frac{1}{2} \left(\frac{1}{2} \right) \left(\frac$



6. Guidelines to win the America's Army game

There is not an absolute way to win the America's Army game, but we could discover some conspicuous tendencies of winners and losers from the data analysis. If we could assume these tendencies are the very strategies of winners or losers, a player or a team can be a winner by adopting winner's tendencies. Because the analysis was conducted at player level, team level, and clan level, the findings can be categorized similarly.

6.1. Strategies for players

Among top players in America's Army game, there are same traits from the viewpoint of weapon usage, communication style, damage control, and role selection. According to the analysis, top players should be able to

- Handle various weapons: from M4 and M16 rifles to M9 pistol and SPR sniper rifle
- Transmit Report-In communications as many times as possible
- Do seeking covers and firing weapons to enemy at the same time
- Keep selecting the medic role if you want to be a medic

6.2. Strategies for teams

Because we could detect some outlier winning teams, we cannot say there are explicit shapes of organization structure of winning teams, but we could reveal several important distinctions between winning teams and losing teams. Winning teams are usually able to

- Be consisted of 10 players to maximize the survival rate
- Fire weapons more frequently and use heavy weapons like RPG7 a lot
- Transmit communications very often: especially Report-In communication

6.3. Strategies for clans

Clans are not organized by America's Army game system, but we could see some players form a clan and play together very often. With considering the existence of the clans, there are some methods to improve the performance of a team.

- Organize a team with same clan member
- Organize a team with players who are in clans if it is impossible to make a team with your clan member.
- Try to reduce the Normal Communications by becoming familiar with your clan member's play style and try to focus on sending the Report-In Communications
- Use both Normal Communications and Report-In Communications frequently if there are team players who are not in your clan

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7. Comparison of America's Army game to Real-world Military Research

This section compares the America's Army analysis with existing research on squad-level interaction among soldiers. This may provide some insights to future research on squad-level team organization. The similarities and the new findings can be categorized into two issues: team structure and communication protocol.

7.1. Structures of America's Army team and squad unit

America's Army team size varies from one to fourteen which is similar to the size of a typical army squad unit, so the squad is an appropriate level for comparison. A great deal of research has been conducted in this area since the end of the World War II. The first modern study was done during the 1946 Infantry Conference, and the recommended squad structure was 9 men consisting of 1 squad leader, 1 assistant squad leader, 1 automatic rifle man, 1 assistant gunner, and 5 rifle men. This squad structure was reformed after the Korean War: from a 9-man squad structure without a sub-teams to a 9-man squad with 2 fire teams as sub-units of the squad. Each fire team consisted of 1 team leader, 1 automatic rifle man, and 2 rifle men. The major reason of this change was the discovery of the importance of heavy weapons such as the automatic rifle, flamethrower, and bazooka. The soldiers with heavier weapons were more effective in combat, [3] so adding one more automatic rifle to the squad structure was considered the effective way to increase fire volume. This tendency, emphasizing the importance of the heavy weapons, could be observed in the America's Army game. Table 16 clearly shows the importance of the heavy weapons: the M2 heavy machine gun, RPK SAW, and RPG7 rocket were all used more frequently by the winning team than the losing team.

Also, the optimal America's Army team size is similar to the recommended army squad unit size. In real world, to determine the army squad size, many factors were considered such as how many soldiers are controlled by one squad leader, how large a size is sustainable and maneuverable with casualties or a pinned down squad leader, and how many soldiers can be carried by an infantry fighting vehicle. The recommended army squad unit sizes is usually between 9 and 13. Table 5 indicates that the most favorable team size of an America's Army team is 10. Table 5 also shows that the 10-man America's Army teams have a relatively high survival ratio even when they are losing and better survival ratio that others when they are winning.

7.2. Communication Patterns of America's Army teams and Army Squads

To date infantryman-level radio usage has not been well researched. Possible reasons for this include the difficulty of collecting well-organized intra-squad radio usage datasets in real-word conditions, and research concentration on the team size and the team equipment rather than intra-squad radio communication. However, we could see the importance of structure, content, and frequency of the intra-squad communication through the data analysis result of America's Army, and there is an increasing demand for the research of the optimal communication protocol in an army squad unit.

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Christ and Evans [4] present one field experiment about using intra-squad radio communication. The research identified 5 tactics, techniques, and procedures concerning the rules for radio discipline (who is permitted to talk at what time), and 13 communication content categories that explain 13 types of message contents. Compared to the America's Army data analysis, we can interpret that the America's Army communication style is equal to the TTP 5, (Free Talk), and Report-In communication in America's Army data analysis is same as the Provide Information (Friend) communication.

As we can see in Figure 32, it is very clear that the frequent Report-In communication is a key to wining the game, and the research from ARI states that the Provide Information (friend) communication was the one of the most frequent communications in squads. At the same time, squad leaders broadcast the Provide Information (friend) communication more frequently than squad members does, and this tendency is also observed and analyzed in the chapter 5.2.2.2. Frequent Report-In top players. Among 100 top players, there were some players who used the Report-In communication very often, and we conjecture that they are taking the role of combat leader.

Though some similarities could be found, the America's Army data analysis chose different approach from ARI research about the communication protocol and structure. ARI research used strict five types of TTP for experiment, and the experiment displays that the TTP 1, "Don't Talk", results the highest situation awareness result. On the other hand, in America's Army, every team follows TTP 5, and the communication network structures of top 1000 teams are investigated. According to the regression analysis, low average distance, high network level, and high sequential edge count can result reduced team received damage. Similarly, low average speed, low closeness centralization, high minimum speed, and high total degree centralization generates increased team inflicted damage. Because the ARI research didn't conducted any rigorous analysis on the communication dynamics or structure, the data analysis of America's Army cannot be compared directly on this matter, but it should be noted that the data analysis of America's Army suggests more detailed squad communication structure shape than the ARI research did.

7.3. Training inexperienced soldiers by using America's Army game

America's Army game is one of the well-known shooting games, and it is freely distributed through on-line game web sites and Army recruiting officers, which makes the game ideal to use a method to introduce and train young adults and inexperienced soldiers. From the above comparisons, we could identify that the game situation is quite similar to the real-world situation. Moreover, the game play style of top players in the America's Army game and the combat style of trained soldiers in real-world are quite similar to each other. For example, there are some top players who send out the Report-In Communication very frequently, and ARI research could reveal squad leaders transmit the Provide Information (Friend) Communication very often. Also, top players are able to seek the covers and to fire the weapons at the same time, which Army wants to make inexperienced soldiers do so. Therefore, it would be a good way to use the America's Army game as a method to train the inexperienced soldiers.

7.4. Comparison between C2 dataset and America's Army dataset

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Command and control (C2) dataset is collected from Fort Lee, Fort Leavenworth, and Fort Knox. This dataset is modeling the brigade level staff officer social network. Even though America's Army dataset is about the squad level army unit, both dataset are analyzed in the perspective of the social network, so it was worth enough to compare each other. From the C2 dataset, it is concluded that physical and social distance, and background similarity, can predict how well people can estimate information about others. In the America's Army dataset, the ORA measures of social network could predict the damage team will receive/inflict. Also, the high clannishness representing the common background among team members was the one of the traits of winning teams. With these similarities, we conjecture that the social network and the background setting are the performance predictors which can be applied to organizations beyond the limitation of size and problem domain.

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8. Conclusion

America's Army dataset is researched at player level, team level, and clan level. Particularly, many statistical methods are applied to discover traits of dynamic social networks of winning teams in America's Army. From the research, several commonalities among top teams were found, and some outlying teams were adopting unusual ways to win.

The player level analyses could reveal that there are several distinguishing characteristics of top players. The characteristics are the variety of weapon selection, dodging bullets and being aggressive at the same time, and transmitting Report-In communication frequently. To be a top player in America's Army game, a player should be able to deal with various weapons, which means they should be equipped with various weapons (obtain high powered weapons from the enemy during the game), and be experienced in using them. Top players are capable of using rifle, sniper rifle, and grenades when they are needed. Not only weapon usage, but also communication style distinguishes the top players: usually top player are very apt to send out their position through the Report-In communication, which means there is more possibility that he can get supports or covering fires from other team members. When it comes to the top players' attack and defense behavior, it is very clear that the top players can inflict good amount of damage toward the opponent without having much damage themselves. We cannot say that how they behave to dodge the bullets and to fire the weapons, but it is quite certain that they are not just attacking without seeking covers or just running away from the combat without attacking the enemies: the top players should be able to fire weapons and to seek the covers at the same time.

The team level analyses have shown that there are some factors which distinguish winning teams from losing teams and which makes the team more efficient and safer. The most favorable size of teams is 10 players, and the 10-men teams are very similar to the size of the squad unit which is specified by the recommendation of Reorganization of the Army Division when it compared to Army squad. The 10-men team has the relatively higher survival ratio than the other sizes of teams have, in both cases, losing and winning. It has been found that some parameters, frequent usage of the weapon, precision of the weapon use, and frequency of communication, can be the distinctions between winning teams and losing teams. High weapon usage is one of the best indicators of winning teams in America's Army game, and this corresponds to the argument that the high volume of weapon fire leads success of the real world squad, which is the common belief of the army officers. Also, the high frequency of Report-In communication is the essential factor to win the games, and this result are very similar to the ARI research which claims that the Provide Information (friend) communications, similar to the Report-In communication, are frequently transmitted by trained soldiers when they can use intra-squad radio communication. By using the Report-In communication, the team will have more chance to have unified situation awareness: where the team members are and how team members can support the other team members. This can lead more effective covering fires, avoiding friendly fires, and medical supports to wounded soldiers.

Additionally, the correlation and regression analyses of the general statistical data and the ORA analysis results suggest some insights in the combat result. For example, the longer the game and more weapon fires in the first part of game lower the entire number of survivals. The regression analyses, between ORA network level measures and team received/inflicted damage,

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suggest that observing Report-In who-talked-after-whom network can be a good way to collect explanatory variables which can predict the amount of team received/inflicted damage. For example, communication structure having high sequential edge count and high network level will reduce team received damage. The shape of that kind of structure will be a long chain of communication line. Also, to enhance the team inflict damage, the long chain shaped communication structure would be good because the team inflicted damage will be increased with a communication structure with high average speed and high closeness centralization.

To identify the alternative ways to win, principal component analysis and correspondence analysis are done. To do the analyses, top 1000 teams are sampled from the dataset, and they are categorized into 10 clusters by using K-means analysis. After the categorization, principal component analysis and correspondence analysis could identify that 6 clusters are very closely located, and the other 4 clusters are remotely located from the other clusters. The 4 clusters can be the outlying teams having unusual aspects in the perspective of team measures, and the unusual aspects of the 4 clusters might be interpreted as the alternative ways to win. For instance, teams in one of the outlying clusters have a communication network with the high reciprocal edge count, high clustering coefficient, and high connectedness: this means that they are using not a chain shaped communication network, but more web shaped communication network.

The clan level analyses strongly suggest that making a team with same clan members is the most effective way to win the. Inherently, there is no functionality to identify players' clan participation in America's Army game. However, in America's Army community, players usually decorate their ID with identical prefix with same clan members. Thus, we develop a parser for players' ID and extract the clan names and participants by identifying the prefix of the players' ID. Being in a same clan, players play together very often, and it results that each player becomes very familiar with the other players' play style. Thus, when they organize an America's Army team and start a game, they just transmit the Report-In communications to the other team members without using the other communication messages to organize their tactical plans, and this makes the team very efficient. In other words, the teams consisted of the same clan members can maximize the frequency of the Report-In communications and gain the benefit of the Report-In communication maximally. The data analysis clearly demonstrates that the teams with same clan members have less casualties and high possibility to win the game. When this is not an option, forming a team with players who are participating in clans is the alternative way to win. When someone is a clan member, it means that he played enough to get involved with certain clans and he certainly have a good knowledge about playing the game. Then, it is quite obvious that the team will win if a team is organized with experienced members. However, in this case, the frequency of Normal communication, communication in natural language, increases to communicate with unfamiliar team members because of the necessity to coordinate their game play plan. These observations displays the importance to organize the squad team with the soldiers who are familiar to each other, so they don't spend valuable time in communicating each other in lengthy words.

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Appendix A – Format of DynetML file used in America's Army

```
<?xml version="1.0" encoding="UTF-8" ?>
<DynamicNetwork>
  <MetaMatrix>
     <nodes>
       <nodeset id="player" type="agent">
         <node id="(a playerid in a team)" />
          <node id="(a playerid in a team)" />
       </nodeset>
       <nodeset id="training" type="knowledge">
         <node id="(marksman or medic)" />
         <node id="(marksman or medic)" />
       </nodeset>
       <nodeset id="weapon" type="resource">
         <node id="(a weapon name)" />
          <node id="(a weapon name)" />
       </nodeset>
       <nodeset id="location" type="location">
         <node id="(a location name)" />
          <node id="(a location name)" />
       </nodeset>
       <nodeset id="objective" type="task">
         <node id="(objective description)" />
       </nodeset>
       <nodeset id="team" type="organization">
         <node id="(team color:blue or red)" />
       </nodeset>
     </nodes>
     <networks>
       <graph sourceType="agent" targetType="agent" id="agent x agent">
         <edge source="(communication sender playerid)" target="(communication receiver playerid)"</pre>
          type="double" value="(number of communication)" />
         <edge source="(communication sender playerid)" target="(communication receiver playerid)"
          type="double" value="(number of communication)" />
       </graph>
       <graph sourceType="agent" targetType="knowledge" id="agent x knowledge">
         <edge source="(playerid)" target="(marksman or medic)" type="double" value="1.000" />
          <edge source="(playerid)" target="(marksman or medic)" type="double" value="1.000" />
       </graph>
       <graph sourceType="agent" targetType="resource" id="agent x resource">
         <edge source="(playerid)" target="(a weapon name)" type="double" value="1.000" />
          <edge source="(playerid)" target="(a weapon name)" type="double" value="1.000" />
       </graph>
     </networks>
  </MetaMatrix>
</DynamicNetwork>
```

Appendix B – List of Measures used in the America's Army project

General Measures (32+16*3=80 measures)	
Factor Name List	The Meaning of the Factor
YYY : Analyzed Game Part	
	1/3 : The first third part of the game
	2/3 : The middle third part of the game
	3/3 : The last third part of the game
Factor Name List	The Meaning of the Factor
Won	Win/lose
Numplayer	Number of player in a team
numMedic	The number of medics in the team
numSoldier	The number of soldiers in the team
ratioMedic	The ratio of medics in the team (numMedic / numPlayers)
ratioSoldier	The ratio of soldiers in the team (numSoldier / numPlayers)
numCommLink	The total number of communication among team members
avgCommLink	The average number of communication among team members (numCommLink / avgCommLink)
numReportInComm	The total number of Report-In communication among team members
avgofReportInComm	The average number of Report-In communication among team members (numReportInComm / numPlayers)
numNormalComm	The total number of Normal Communication among team members
avgofNormalComm	The average number of Normal Communication among team members (numNormalComm / numPlayers)
1/3avgofreportin	The average number of Report-In communication among team members during the first period of game (First_reportIn / numPlayers)
1/3avgofnormalComm	The average number of Normal communication among team members during the first period of game (First_reportIn / numPlayers)
2/3avgofreportin	The average number of Report-In communication among team members during the second period of game (Second_reportIn / numPlayers)
2/3avgofnormalComm	The average number of Normal communication among team members during the second period of game (Second_reportIn / numPlayers)
3/3avgofreportin	The average number of Report-In communication among team members during the last period of game (Third_reportIn / numPlayers)
3/3avgofnormalComm	The average number of Normal communication among team members during the last period of game (Third_reportIn / numPlayers)
numsurvive	Number of survival after the game
avgsurvive	Ratio of survival after the game
Numkill	Number of killed opponent player
Avgkill	Ratio of killed opponent player
Totalscore	Total score
Avgtotalscore	Average of total score
goalsscore	Goal score
Avggoalscore	Average of goal score
Killsscore	Kill score
Avgkillsscore	Average of kill score
Roescore	ROE score
Avgroescore	Average of ROE score
Lengthgame	Game length
YYY_shots	The number of shots during the period

YYY_kills	The number of opponent kills during the period					
YYY_dmg	The amount of damage inflicted on the opponent team during the period					
YYY_ratioshotsreportin	Ratio of shot vs. number of report-in					
YYY_ratioshotsnormalcomm	Ratio of shot vs. number of normal comm.					
YYY_ratioshotstotalcomm	Ratio of shot vs. number of total comm.					
YYY_ratiokillsreportin	Ratio of kill vs. number of report-in					
YYY_ratiokillsnormalcomm	Ratio of kill vs. number of normal comm.					
YYY_ratiokillstotalcomm	Ratio of kill vs. number of total comm.					
YYY_ratiodmgreportin	Ratio of damage vs. number of report-in					
YYY_ratiodmgnormalcomm	Ratio of damage vs. number of normal comm.					
YYY_ratiodmgtotalcomm	Ratio of damage vs. number of total comm.					
YYY_totalComm	The total number of communication among team members during the first priod of game					
YYY_ratioreportinnormalcomm	Ratio of Reportin vs. normal comm.					
YYY_reportIn	The total number of Report-In communication among team members during the first period of game					
YYY_normalComm	The total number of Normal Communication among team members during the first period of game					
ORA Measures (Agent Level) (27*4=108 measures)						
YYY: The Category of the Statistics						
	Min : The minimum value of the factor in the team					
	Max : The maximum value of the factor in the team					
	Average : The average value of the factor for the team					
	Total : The total value of the factor for the team					
Factor Name List	The Meaning of the Factor					
Tuotor Humo Elot	The meaning of the Factor					
AgentLevel_YYY_agentSocioEconomicPower	The meaning of the Factor					
	Across all agent pairs that have a shortest path containing this agent, the percentage that pass through this agent.					
AgentLevel_YYY_agentSocioEconomicPower	Across all agent pairs that have a shortest path containing this agent, the percentage that pass through this agent. Compute the number of distinct cliques to which each node in a square					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass through this agent.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount	Across all agent pairs that have a shortest path containing this agent, the percentage that pass through this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass through this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network. The In Degree Centrality of an agent in an unimodal network is its normalized in-degree. Calculate the Stephenson and Zelen information centrality measure for each agent. Interlocker in a square network have a high Triad Count, respectively.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality AgentLevel_YYY_informationCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network. The In Degree Centrality of an agent in an unimodal network is its normalized in-degree. Calculate the Stephenson and Zelen information centrality measure for each agent. Interlocker in a square network have a high Triad Count, respectively. The average closeness of an agent to the other agents in a network. Inverse Closeness is the sum of the inverse distance between an agent and all other agents.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality AgentLevel_YYY_informationCentrality AgentLevel_YYY_interlockers	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network. The In Degree Centrality of an agent in an unimodal network is its normalized in-degree. Calculate the Stephenson and Zelen information centrality measure for each agent. Interlocker in a square network have a high Triad Count, respectively. The average closeness of an agent to the other agents in a network. Inverse Closeness is					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality AgentLevel_YYY_informationCentrality AgentLevel_YYY_interlockers AgentLevel_YYY_inverseClosenessCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network. The In Degree Centrality of an agent in an unimodal network is its normalized in-degree. Calculate the Stephenson and Zelen information centrality measure for each agent. Interlocker in a square network have a high Triad Count, respectively. The average closeness of an agent to the other agents in a network. Inverse Closeness is the sum of the inverse distance between an agent and all other agents. Boolean value which is true if an agent is the only agent who knows a piece of knowledge and who is known by exactly one other agent. The one agent known also has its KAI set to one. Detects agents who have singular knowledge					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality AgentLevel_YYY_informationCentrality AgentLevel_YYY_interlockers AgentLevel_YYY_inverseClosenessCentrality AgentLevel_YYY_inverseClosenessCentrality	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network. The In Degree Centrality of an agent in an unimodal network is its normalized in-degree. Calculate the Stephenson and Zelen information centrality measure for each agent. Interlocker in a square network have a high Triad Count, respectively. The average closeness of an agent to the other agents in a network. Inverse Closeness is the sum of the inverse distance between an agent and all other agents. Boolean value which is true if an agent is the only agent who knows a piece of knowledge and who is known by exactly one other agent. The one agent known also has its KAI set to one.					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality AgentLevel_YYY_informationCentrality AgentLevel_YYY_interlockers AgentLevel_YYY_inverseClosenessCentrality AgentLevel_YYY_knowledgeAccessIndex AgentLevel_YYY_knowledgeExclusivity	Across all agent pairs that have a shortest path containing this agent, the percentage that pass throgh this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network. The In Degree Centrality of an agent in an unimodal network is its normalized in-degree. Calculate the Stephenson and Zelen information centrality measure for each agent. Interlocker in a square network have a high Triad Count, respectively. The average closeness of an agent to the other agents in a network. Inverse Closeness is the sum of the inverse distance between an agent and all other agents. Boolean value which is true if an agent is the only agent who knows a piece of knowledge and who is known by exactly one other agent. The one agent known also has its KAI set to one. Detects agents who have singular knowledge The Node Level for an agent v in a square network is the longest shortest path from v to					
AgentLevel_YYY_agentSocioEconomicPower AgentLevel_YYY_betweennessCentrality AgentLevel_YYY_cliqueCount AgentLevel_YYY_closenessCentrality AgentLevel_YYY_cognitiveLoad AgentLevel_YYY_constraint AgentLevel_YYY_effectiveNetworkSize AgentLevel_YYY_eigenvectorCentrality AgentLevel_YYY_inDegreeCentrality AgentLevel_YYY_informationCentrality AgentLevel_YYY_interlockers AgentLevel_YYY_inverseClosenessCentrality AgentLevel_YYY_knowledgeAccessIndex AgentLevel_YYY_knowledgeExclusivity AgentLevel_YYY_nodeLevels	Across all agent pairs that have a shortest path containing this agent, the percentage that pass through this agent. Compute the number of distinct cliques to which each node in a square The average closeness of an agent to the other agent in a network. Loosely, Closeness is the inverse of the average distance in the network between the agent and all other agents. Measures the total amount of effort expended by each agent to do its tasks. The degree to which each node in a square network is constrained from acting because of its existing links to other nodes The effective size of a agent's ego network based on redundancy of ties. Calculates the eigenvector of the largest positive eigenvector of the adjacency matrix representation of a square network. The In Degree Centrality of an agent in an unimodal network is its normalized in-degree. Calculate the Stephenson and Zelen information centrality measure for each agent. Interlocker in a square network have a high Triad Count, respectively. The average closeness of an agent to the other agents in a network. Inverse Closeness is the sum of the inverse distance between an agent and all other agents. Boolean value which is true if an agent is the only agent who knows a piece of knowledge and who is known by exactly one other agent. The one agent known also has its KAI set to one. Detects agents who have singular knowledge The Node Level for an agent v in a square network is the longest shortest path from v to every agent v can reach. If v cannot reach any agents, then its level is 0.					

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The degree of dissimilarity between agents based on shared knowledge. Each agent computes to what degree the other agents know what they do not know.				
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3/3 : The last third part of the game The Meaning of the Factor				
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XXXXX_YYY_skipEdgeCount	The fraction of edges in a unimodal network that skip levels. An edge (i,j) is a skip edge if there is a path from node i to node j even after the edge (i,j) is removed.				
XXXXX_YYY_spanOfControl	The average number of out edges per agent with non-zero out degrees.				
XXXXX_YYY_strongComponentCount	The number of strongly connected components in a network.				
XXXXX_YYY_totalDegreeCentralization	A centralization of a square network based on total degree centrality of each node.				
XXXXX_YYY_transitivity	The percentage of edge pairs { (i,j) , (j,k) } in the network such that (i,k) is also an edge in the network.				
XXXXX_YYY_upperBoundedness	The degree to which pairs of agents have a common ancestor.				
XXXXX_YYY_weakComponentCount	The number of weakly connected components in a network.				
XXXXX_YYY_knowledgeDiversity	The distribution of difference in idea sharing. This is the Herfindahl-Hirshman index applied to column sums of AK.				
XXXXX_YYY_knowledgeLoad	Average number of knowledge per agent.				
XXXXX_YYY_knowledgeRedundancy	Average number of redundant agents per knowledge. An agent is redundant if there is already an agent that has the knowledge.				
XXXXX_YYY_accessRedundancy	Average number of redundant agents per resource. An agent is redundant if there is already an agent that has access to the resource.				
XXXXX_YYY_resourceDiversity	The distribution of difference in resource sharing. This is the Herfindahl-Hirshman index applied to column sums of AR				
XXXXX_YYY_resourceLoad	Average number of resources per agent.				

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Appendix C – Correlation analysis results between team performance measures and team organizational measures

Table C-1 Top 20 Correlations between the *Number of the Survived Players* and Various Measures (Winners)

	Winners	Winners		Winners (Small)		Winners (Medium)		Winners (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	
1	numSoldier	0.548	numSoldier	0.3661	lengthGame	-0.472	lengthGame	-0.524	
2	AgentLevel Total weakComponentMembers	0.4933	lengthGame	-0.318	First shots	-0.359	First shots	-0.483	
3	NormalComm 3/3 weakComponentCount	0.4614	AgentLevel Min knowledgeExclusivity	-0.317	avgofNormalComm	-0.328	avgCommLink	-0.393	
4	NormalComm 3/3 strongComponentCount	0.4576	AgentLevel Total weakComponentMembers	0.2732	3/3avgofnormalComm	-0.313	avgofNormalComm	-0.376	
5	NormalComm 2/3 weakComponentCount	0.452	AgentLevel Average knowledgeExclusivity	-0.265	avgCommLink	-0.312	3/3avgofnormalComm	-0.368	
6	ReportIn 1/3 weakComponentCount	0.4516	Third reporting	0.2533	numNormalComm	-0.299	numCommLink	-0.366	
7	AgentLevel Max weakComponentMembers	0.4495	ReportIn 3/3 networkLevels	0.2525	numSoldier	0.2861	numNormalComm	-0.352	
8	NormalComm 2/3 strongComponentCount	0.4389	AgentLevel Min resourceExclusivity	-0.239	2/3avgofnormalComm	-0.284	Third normalComm	-0.348	
9	ReportIn 1/3 strongComponentCount	0.4386	ReportIn 3/3 averageDistance	0.239	Third normalComm	-0.282	2/3avgofnormalComm	-0.341	
10	NormalComm 1/3 weakComponentCount	0.4335	ReportIn 1/3 knowledgeRedundancy	0.2342	numCommLink	-0.272	Second normalComm	-0.325	
11	NormalComm 1/3 strongComponentCount	0.4232	ReportIn 2/3 knowledgeRedundancy	0.2342	Second normalComm	-0.268	First totalComm	-0.322	
12	AgentLevel Average weakComponentMembers	0.4221	ReportIn 3/3 knowledgeRedundancy	0.2342	First totalComm	-0.253	1/3avgofreportin	-0.301	
13	ReportIn 1/3 knowledgeRedundancy	0.4125	NormalComm 1/3 knowledgeRedundancy	0.2342	AgentLevel Total weakComponentMembers	0.2382	NormalComm 2/3 totalDegreeCentralization1	-0.299	
14	ReportIn 2/3 knowledgeRedundancy	0.4125	NormalComm 2/3 knowledgeRedundancy	0.2342	1/3avgofreportin	-0.234	NormalComm 2/3 inDegreeCentralization	-0.297	
15	ReportIn 3/3 knowledgeRedundancy	0.4125	NormalComm 3/3 knowledgeRedundancy	0.2342	NormalComm 3/3 clusteringCoefficient	-0.233	NormalComm 2/3 outDegreeCentralization	-0.296	
16	NormalComm 1/3 knowledgeRedundancy	0.4125	ReportIn 3/3 spanOfControl	0.23	NormalComm 3/3 totalDegreeCentralization1	-0.231	NormalComm 3/3 clusteringCoefficient	-0.294	
17	NormalComm 2/3 knowledgeRedundancy	0.4125	AgentLevel Total relativeSimilarity	0.2286	NormalComm 2/3 totalDegreeCentralization1	-0.228	NormalComm 3/3 totalDegreeCentralization1	-0.292	
18	NormalComm 3/3 knowledgeRedundancy	0.4125	AgentLevel Average relativeExpertise	-0.225	NormalComm 2/3 inDegreeCentralization	-0.225	NormalComm 2/3 spanOfControl	-0.292	
19	NormalComm 3/3 diameter	0.412	AgentLevel Min relativeExpertise	-0.225	AgentLevel Total interlockers	0.2241	First reporting	-0.287	
20	ReportIn 1/3 diameter	0.4118	AgentLevel Max relativeExpertise	-0.225	NormalComm 2/3 outDegreeCentralization	-0.224	NormalComm 2/3 closenessCentralization	-0.287	

Table C-2 Top 20 Correlations between the *Number of the Survived Players* and Various Measures (Losers)

	Losers		Losers (Small)		Losers (Medium)		Losers (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	lengthGame	-0.362	ReportIn 1/3 resourceLoad	-0.176	lengthGame	-0.405	lengthGame	-0.536
2	numSoldier	0.3541	ReportIn 2/3 resourceLoad	-0.176	First shots	-0.316	First shots	-0.474
3	Third shots	0.3055	ReportIn 3/3 resourceLoad	-0.176	numSoldier	0.2614	avgCommLink	-0.383
4	NormalComm 3/3 weakComponentCount	0.2982	NormalComm 1/3 resourceLoad	-0.176	avgCommLink	-0.257	numCommLink	-0.378
5	Third ratioDmgNormalComm!	0.2955	NormalComm 2/3 resourceLoad	-0.176	avgofNormalComm	-0.256	numMedic	-0.354
6	AgentLevel Total weakComponentMembers	0.2918	NormalComm 3/3 resourceLoad	-0.176	numNormalComm	-0.243	avgofNormalComm	-0.346
7	NormalComm 3/3 strongComponentCount	0.2904	AgentLevel Min resourceExclusivity	-0.174	numCommLink	-0.24	ratioMedic	-0.346
8	ReportIn 1/3 weakComponentCount	0.2898	Third reporting	0.1601	3/3avgofnormalComm	-0.232	ratioSoldier	0.3457
9	AgentLevel Max weakComponentMembers	0.2885	ReportIn 3/3 networkLevels	0.151	2/3avgofnormalComm	-0.223	AgentLevel Total knowledgeExclusivity	0.3445
10	NormalComm 2/3 weakComponentCount	0.2868	numSoldier	0.1462	First totalComm	-0.223	numNormalComm	-0.341
11	Third ratioDmgTotalComm	0.2848	lengthGame	-0.145	Third normalComm	-0.218	NormalComm 2/3 averageDistance	-0.337
12	AgentLevel Average weakComponentMembers	0.2764	ReportIn 3/3 averageDistance	0.1434	ReportIn 1/3 resourceLoad	-0.218	NormalComm 2/3 spanOfControl	-0.336
13	Third ratioKillNormalComm	0.2689	3/3avgofreportin	0.1413	ReportIn 2/3 resourceLoad	-0.218	AgentLevel Average knowledgeExclusivity	0.3326
14	NormalComm 1/3 weakComponentCount	0.2675	ReportIn 3/3 spanOfControl	0.1391	ReportIn 3/3 resourceLoad	-0.218	First totalComm	-0.331
15	NormalComm 2/3 strongComponentCount	0.2643	ReportIn 3/3 averageSpeed	0.13	NormalComm 1/3 resourceLoad	-0.218	AgentLevel Total informationCentrality	-0.322
16	ReportIn 1/3 strongComponentCount	0.2637	ReportIn 3/3 totalDegreeCentralization	0.1293	NormalComm 2/3 resourceLoad	-0.218	NormalComm 2/3 averageSpeed	-0.319
17	Third ratioShotsNormalComm	0.2576	3/3avgofnormalComm	-0.125	NormalComm 3/3 resourceLoad	-0.218	AgentLevel Average informationCentrality1	-0.318
18	Third ratioKillTotalComm!	0.2567	ReportIn 3/3 minimumSpeed	0.1235	Second normalComm	-0.217	Second totalComm	-0.318
19	Third ratioDmgReportIn	0.2528	ReportIn 1/3 resourceDiversity	-0.123	Third shots	0.2086	3/3avgofnormalComm	-0.317
20	NormalComm 1/3 strongComponentCount	0.2509	ReportIn 2/3 resourceDiversity	-0.123	Third ratioDmgTotalComm	0.2046	2/3avgofnormalComm	-0.317

Table C-3 Top 20 Correlations between the Average of the Survived Players and Various Measures (Winners)

	Winners		Winners (Small)		Winners (Medium)	Winners (Large	e)
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	lengthGame	-0.52	lengthGame	-0.39	lengthGame	-0.505	AgentLevel_Min_simmeli anTies	-0.576
2	First_shots	-0.485	First_shots	-0.315	First_shots	-0.434	AgentLevel_Average_inf ormationCentrality1	-0.532
3	numCommLink	-0.394	numNormalComm	-0.234	avgofNormalComm	-0.33	NormalComm_2/3_recipr ocalEdgeCount	-0.424
4	numNormalComm	-0.38	Third_normalComm	-0.234	3/3avgofnormalComm	-0.315	Third_ratioShotsNormalC omm	-0.424
5	Third_normalComm	-0.371	numCommLink	-0.23	avgCommLink	-0.307	First_ratioKillNormalCom m	-0.409
6	First_totalComm	-0.354	First_totalComm	-0.213	numNormalComm	-0.344	NormalComm_3/3_avera geDistance	-0.406
7	Second_normalComm	-0.336	Second_normalComm	-0.195	numSoldier	-0.014	AgentLevel_Total_inDegr eeCentrality	-0.394
8	Second_totalComm	-0.314	First_ratioShotsTotalCom m	-0.194	2/3avgofnormalComm	-0.293	ReportIn_1/3_inDegreeC entralization	-0.393
9	First_reportIn	-0.308	First_ratioDmgTotalComm	-0.193	Third_normalComm	-0.328	NormalComm_2/3_betw eennessCentralization1	-0.378
10	NormalComm_2/3_spanOf Control	-0.299	avgofNormalComm	-0.193	numCommLink	-0.328	AgentLevel_Total_constr aint	-0.371
11	NormalComm_2/3_averag eDistance	-0.295	3/3avgofnormalComm	-0.19	Second_normalComm	-0.303	AgentLevel_Average_inv erseClosenessCentrality	-0.37
12	NormalComm_3/3_spanOf Control	-0.293	numSoldier	-0.19	First_totalComm	-0.3	AgentLevel_Max_relative Similarity	-0.34
13	avgCommLink	-0.291	ReportIn_3/3_connectedn ess	0.1876	AgentLevel_Total_weakCo mponentMembers	0.0169	Second_ratioShotsReportIn	-0.336
14	AgentLevel_Max_effective NetworkSize	-0.29	First_ratioDmgReportIn	-0.186	1/3avgofreportin	-0.239	ReportIn_3/3_accessRed undancy	-0.331
15	avgofNormalComm	-0.29	First_ratioShotsReportIn1	-0.186	NormalComm_3/3_clusteri ngCoefficient	-0.245	NormalComm_3/3_acces sRedundancy	-0.33
16	NormalComm_3/3_lateralE dgeCount	-0.29	First_reportIn	-0.185	NormalComm_3/3_totalDe greeCentralization1	-0.241	NormalComm_2/3_hierar chy1	-0.329
17	NormalComm_3/3_networ kLevels	-0.287	avgCommLink	-0.184	NormalComm_2/3_totalDe greeCentralization1	-0.244	AgentLevel_Max_cogniti veLoad	-0.328
18	First_ratioShotsNormalCo mm	-0.285	First_ratioDmgNormalCo mm!	-0.184	NormalComm_2/3_inDegr eeCentralization	-0.239	AgentLevel_Average_co gnitiveLoad	-0.327
19	NormalComm_2/3_networ kLevels	-0.284	First_ratioShotsNormalCo mm	-0.181	AgentLevel_Total_interlock ers	0.1484	NormalComm_2/3_stron gComponentCount	-0.325
20	AgentLevel_Total_constraint	-0.283	First_ratioKillTotalComm!	-0.18	NormalComm_2/3_outDeg reeCentralization	-0.237	Second_ratioDmgTotalC omm!	-0.316

Table C-4 Top 20 Correlations between the Average of the Survived Players and Various Measures (Losers)

	Losers		Losers (Small)		Losers (Medium)		Losers (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	lengthGame	-0.383	ReportIn_1/3_resourceLoad	-0.194	lengthGame	-0.409	lengthGame	-0.545
2	First_shots	-0.298	ReportIn_2/3_resourceLoad	-0.194	First_shots	-0.327	First_shots	-0.483
3	avgofNormalComm	-0.246	ReportIn_3/3_resourceLoad	-0.194	avgofNormalComm	-0.257	numCommLink	-0.389
4	avgCommLink	-0.24	NormalComm_1/3_resource Load	-0.194	numNormalComm	-0.253	avgCommLink	-0.388
5	numNormalComm	-0.23	NormalComm_2/3_resource Load	-0.194	avgCommLink	-0.253	numMedic	-0.376
6	3/3avgofnormalComm	-0.228	NormalComm_3/3_resource Load	-0.194	numCommLink	-0.25	AgentLevel_Total_knowledg eExclusivity	0.3616
7	numCommLink	-0.227	ReportIn_1/3_resourceDiver sity	-0.169	3/3avgofnormalComm	-0.233	AgentLevel_Average_knowle dgeExclusivity	0.3579
8	ReportIn_1/3_resourceLoad	-0.223	ReportIn_2/3_resourceDiver sity	-0.169	First_totalComm	-0.232	avgofNormalComm	-0.352
9	ReportIn_2/3_resourceLoad	-0.223	ReportIn_3/3_resourceDiver sity	-0.169	Third_normalComm	-0.229	ratioMedic	-0.351
10	ReportIn_3/3_resourceLoad	-0.223	NormalComm_1/3_resource Diversity	-0.169	2/3avgofnormalComm	-0.225	ratioSoldier	0.3513
11	NormalComm_1/3_resourceLoad	-0.223	NormalComm_2/3_resource Diversity	-0.169	Second_normalComm	-0.225	numNormalComm	-0.35
12	NormalComm_2/3_resourceL oad	-0.223	NormalComm_3/3_resource Diversity	-0.169	ReportIn_1/3_resourceLoad	-0.223	NormalComm_2/3_average Distance	-0.345
13	NormalComm_3/3_resourceL oad	-0.223	lengthGame	-0.145	ReportIn_2/3_resourceLoad	-0.223	NormalComm_2/3_spanOfC ontrol	-0.344
14	Third_ratioDmgNormalComm !	0.2207	AgentLevel_Min_resourceEx clusivity	-0.142	ReportIn_3/3_resourceLoad	-0.223	First_totalComm	-0.341
15	Third_ratioDmgTotalComm	0.2192	3/3avgofreportin	0.1376	NormalComm_1/3_resourceL oad	-0.223	AgentLevel_Total_informationCentrality	-0.331
16	First_totalComm	-0.215	Third_reportIn	0.1358	NormalComm_2/3_resourceL oad	-0.223	Second_totalComm	-0.328
17	2/3avgofnormalComm	-0.212	3/3avgofnormalComm	-0.133	NormalComm_3/3_resourceL oad	-0.223	NormalComm_2/3_averageS peed	-0.327
18	Second_normalComm	-0.211	ReportIn_3/3_networkLevels	0.1305	Second_totalComm	-0.207	ReportIn_1/3_spanOfControl	-0.325
19	Third_normalComm	-0.211	Third_normalComm	-0.127	NormalComm_2/3_averageDi stance	-0.202	Third_normalComm	-0.324
20	Third_shots	0.2078	ReportIn_3/3_averageDistan ce	0.1253	First_ratioDmgTotalComm	-0.201	AgentLevel_Average_inform ationCentrality1	-0.324

Table C-5 Top 20 Correlations between the Number of the Killed Opponent Players and Various Measures (Winners)

	Winners		Winners (Small)	ı	Winners (Medium)	Winners (Large	e)
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	First_shots	0.6605	Second_shots	0.4486	First_shots	0.5411	AgentLevel_Average_inf ormationCentrality1	0.6274
2	numMedic	0.6472	First_shots	0.4133	Second_shots	0.4794	AgentLevel_Min_simmeli anTies	0.545
3	numSoldier	0.6304	numSoldier	0.4128	lengthGame	0.4382	AgentLevel_Min_relative Expertise	0.5294
4	Second_shots	0.6293	Third_shots	0.38	Third_totalComm	0.353	NormalComm_1/3_span OfControl	0.499
5	Third_totalComm	0.5437	AgentLevel_Min_knowled geExclusivity	-0.356	Second_totalComm	0.3507	ReportIn_1/3_averageDi stance	0.4832
6	ReportIn_2/3_knowledgeR edundancy	0.5405	AgentLevel_Average_kno wledgeExclusivity	-0.311	numCommLink	0.3411	Second_ratioShotsReportIn	0.4812
7	NormalComm_3/3_knowle dgeRedundancy	0.5405	Second_ratioKillTotalCom m	0.2885	numReportInComm	0.3353	NormalComm_1/3_sequentialEdgeCount	0.4563
8	NormalComm_2/3_knowle dgeRedundancy	0.5405	numCommLink	0.2832	numMedic	0.324	avgofNormalComm	-0.444
9	NormalComm_1/3_knowle dgeRedundancy	0.5405	AgentLevel_Total_weakC omponentMembers	0.2809	NormalComm_1/3_access Redundancy	0.3208	NormalComm_2/3_betw eennessCentralization1	0.4426
10	ReportIn_3/3_knowledgeR edundancy	0.5405	Second_ratioDmgTotalCo mm!	0.2801	NormalComm_3/3_access Redundancy	0.3208	NormalComm_1/3_acces sRedundancy	0.4422
11	ReportIn_1/3_knowledgeR edundancy	0.5405	First_ratioDmgTotalComm	0.2761	ReportIn_3/3_accessRedu ndancy	0.3208	AgentLevel_Min_inverse ClosenessCentrality	-0.427
12	ReportIn_2/3_diameter	0.5245	NormalComm_1/3_access Redundancy	0.268	ReportIn_1/3_accessRedu ndancy	0.3208	Third_ratioShotsNormalC omm	0.4252
13	NormalComm_3/3_diamet er	0.5245	NormalComm_3/3_access Redundancy	0.268	NormalComm_2/3_access Redundancy	0.3208	majorityRatio	0.4179
14	ReportIn_3/3_diameter	0.5244	ReportIn_3/3_accessRedu ndancy	0.268	ReportIn_2/3_accessRedu ndancy	0.3208	Third_ratioKillReportIn	0.4159
15	NormalComm_1/3_diamet er	0.5243	ReportIn_1/3_accessRedu ndancy	0.268	First_totalComm	0.3191	NormalComm_1/3_weak ComponentCount	-0.414
16	ReportIn_1/3_diameter	0.5242	NormalComm_2/3_access Redundancy	0.268	First_ratioDmgReportIn	0.3164	NormalComm_1/3_hierar chy1	0.4134
17	NormalComm_2/3_diamet er	0.5242	ReportIn_2/3_accessRedu ndancy	0.268	AgentLevel_Max_knowled geExclusivity	-0.313	ReportIn_2/3_interdepen dence	0.4129
18	AgentLevel_Max_knowled geExclusivity	-0.523	First_ratioKillTotalComm!	0.268	First_ratioDmgTotalComm	0.3115	AgentLevel_Average_clo senessCentrality	0.4116
19	numReportInComm	0.5178	lengthGame	0.2677	First_ratioDmgNormalCom m!	0.3108	3/3avgofnormalComm	0.4088
20	Second_totalComm	0.5151	Second_ratioKillReportIn1	0.2669	First_ratioKillReportIn	0.3101	AgentLevel_Min_closene ssCentrality	0.4041

Table C-6 Top 20 Correlations between the *Number of the Killed Opponent* and Various Measures (Losers)

	Losers		Losers (Small)		Losers (Medium)		Losers (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	First_shots	0.7078	First_shots	0.5461	First_shots	0.6319	First_shots	0.6889
2	Second_shots	0.596	Second_shots	0.4831	lengthGame	0.4997	lengthGame	0.5727
3	numSoldier	0.5926	lengthGame	0.4007	Second_shots	0.4695	Second_totalComm	0.4825
4	numMedic	0.5501	First_ratioDmgTotalComm	0.3665	First_ratioKillNormalComm	0.3851	Second_shots	0.4758
5	numCommLink	0.5257	First_ratioKillTotalComm!	0.3625	First_ratioDmgNormalComm!	0.384	numCommLink	0.4593
6	Second_totalComm	0.5127	Second_ratioKillTotalComm	0.3396	First_ratioKillReportIn	0.3785	First_totalComm	0.4591
7	lengthGame	0.5104	numSoldier	0.3351	Second_totalComm	0.3771	numReportInComm	0.4537
8	ReportIn_1/3_knowledgeRed undancy	0.4942	First_ratioDmgReportIn	0.335	First_ratioDmgReportIn	0.377	Third_totalComm	0.4327
9	ReportIn_2/3_knowledgeRed undancy	0.4942	First_ratioShotsTotalComm	0.3334	numCommLink	0.3763	avgCommLink	0.4246
10	ReportIn_3/3_knowledgeRed undancy	0.4942	First_ratioKillReportIn	0.3309	First_ratioKillTotalComm!	0.3712	avgofReportInComm	0.4228
11	NormalComm_1/3_knowledg eRedundancy	0.4942	First_ratioDmgNormalComm !	0.3226	First_ratioDmgTotalComm	0.3657	First_reportIn	0.4184
12	NormalComm_2/3_knowledg eRedundancy	0.4942	First_ratioKillNormalComm	0.3177	First_ratioShotsNormalComm	0.3655	First_ratioKillNormalComm	0.4157
13	NormalComm_3/3_knowledg eRedundancy	0.4942	Second_ratioDmgTotalCom m!	0.3158	First_totalComm	0.3609	numNormalComm	0.4151
14	Third_totalComm	0.4864	First_ratioShotsReportIn1	0.3125	First_ratioShotsReportIn1	0.3581	First_ratioDmgNormalComm !	0.4124
15	First_totalComm	0.4858	numCommLink	0.305	numReportInComm	0.3515	AgentLevel_Max_effectiveN etworkSize	0.3986
16	numReportInComm	0.4849	First_ratioShotsNormalCom m	0.2988	First_ratioShotsTotalComm	0.3444	1/3avgofreportin	0.3939
17	NormalComm_3/3_diameter	0.4849	Second_ratioKillReportIn1	0.2977	Third_totalComm	0.3334	ReportIn_1/3_spanOfControl	0.3928
18	ReportIn_2/3_diameter	0.4848	Second_ratioKillNormalCom m	0.2965	numNormalComm	0.3279	AgentLevel_Total_constraint	0.3927
19	NormalComm_1/3_diameter	0.4848	Second_ratioShotsTotalCom m	0.2924	First_reportIn	0.3241	First_ratioShotsNormalCom m	0.3924
20	NormalComm_2/3_diameter	0.4847	AgentLevel_Min_knowledge Exclusivity	-0.292	avgCommLink	0.3088	avgofNormalComm	0.3902

Table C-7 Top 20 Correlations between the Average of the Killed Opponent Players and Various Measures (Winners)

	Winners		Winners (Small)		Winners (Medium)	Winners (Large	e)
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	First_shots	0.4003	Third_shots	0.3441	First_shots	0.4778	AgentLevel_Average_inf ormationCentrality1	0.6093
2	lengthGame	0.3998	Second_shots	0.3119	lengthGame	0.4522	AgentLevel_Min_simmeli anTies	0.5232
3	Second_shots	0.333	First_shots	0.2889	Second_shots	0.4132	AgentLevel_Min_relative Expertise	0.5182
4	avgCommLink	0.2878	AgentLevel_Min_resource Exclusivity	0.2403	avgCommLink	0.3125	NormalComm_1/3_acces sRedundancy	0.4431
5	avgofReportInComm	0.2663	lengthGame	0.2319	numCommLink	0.2986	ReportIn_1/3_averageDi stance	0.4406
6	Second_totalComm	0.2566	Third_ratioKillTotalComm!	0.1977	Second_totalComm	0.2985	NormalComm_1/3_span OfControl	0.4394
7	Third_totalComm	0.2507	Third_ratioKillNormalCom m	0.1957	Third_totalComm	0.2945	Second_ratioShotsRepor tln	0.4289
8	First_ratioDmgTotalComm	0.2491	Third_ratioDmgTotalCom m	0.1954	First_ratioDmgTotalComm	0.2856	NormalComm_1/3_hierar chy1	0.3936
9	numReportInComm	0.2479	Third_ratioDmgNormalCo mm!	0.1915	First_ratioKillTotalComm!	0.2814	NormalComm_2/3_betw eennessCentralization1	0.3928
10	First_ratioKillTotalComm!	0.2472	First_ratioDmgTotalComm	0.1861	avgofReportInComm	0.2806	Third_ratioKillReportIn	0.3909
11	avgofNormalComm	0.2453	First_ratioKillTotalComm!	0.1837	First_totalComm	0.279	ReportIn_2/3_strongCom ponentCount	0.3892
12	AgentLevel_Total_interlock ers	-0.244	Second_ratioKillTotalCom m	0.183	First_ratioDmgReportIn	0.2779	ReportIn_2/3_interdepen dence	0.3869
13	First_totalComm	0.2436	Third_ratioShotsTotalCom m	0.1827	numReportInComm	0.2766	majorityRatio	0.3866
14	First_ratioShotsTotalCom m	0.243	First_ratioShotsTotalCom m	0.1793	First_ratioShotsTotalCom m	0.2755	AgentLevel_Min_inverse ClosenessCentrality	-0.379
15	First_ratioDmgReportIn	0.2414	Third_ratioShotsNormalComm	0.1785	First_ratioKillReportIn	0.2739	AgentLevel_Average_clo senessCentrality	0.3763
16	First_ratioKillReportIn	0.2392	avgCommLink	0.177	First_ratioShotsReportIn1	0.2687	AgentLevel_Average_ag entSocioEconomicPower	0.376
17	First_ratioShotsReportIn1	0.2358	Second_ratioDmgTotalCo mm!	0.1752	avgofNormalComm	0.2631	NormalComm_2/3_recipr ocalEdgeCount	0.3754
18	numCommLink	0.2337	Second_ratioShotsTotalC omm	0.1659	Third_shots	0.262	ReportIn_3/3_strongCom ponentCount	0.3748
19	First_ratioDmgNormalCom m!	0.2291	First_ratioDmgReportIn	0.1597	First_ratioDmgNormalCom m!	0.2593	AgentLevel_Min_closene ssCentrality	0.3745
20	1/3avgofreportin	0.2262	First_ratioKillReportIn	0.1588	NormalComm_1/3_access Redundancy	0.2572	ReportIn_3/3_diameter	0.3744

Table C-8 Top 20 Correlations between the Average of the Killed Opponent and Various Measures (Losers)

	Losers		Losers (Small)		Losers (Medium)		Losers (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	First_shots	0.5818	First_shots	0.4909	First_shots	0.602	First_shots	0.6709
2	lengthGame	0.4992	Second_shots	0.4395	lengthGame	0.5109	lengthGame	0.552
3	Second_shots	0.4587	lengthGame	0.3838	Second_shots	0.4371	Second_shots	0.463
4	Second_totalComm	0.3736	First_ratioDmgTotalComm	0.3273	First_ratioKillTotalComm!	0.3608	Second_totalComm	0.4413
5	numCommLink	0.3733	First_ratioKillTotalComm!	0.3263	First_ratioKillNormalComm	0.3593	numReportInComm	0.429
6	First_ratioKillNormalComm	0.361	Second_ratioKillTotalComm	0.3001	First_ratioKillReportIn	0.3586	avgofReportInComm	0.4264
7	First_ratioDmgNormalComm!	0.3596	First_ratioShotsTotalComm	0.2979	First_ratioDmgNormalComm!	0.3557	First_totalComm	0.4192
8	First_totalComm	0.3592	First_ratioDmgReportIn	0.2932	First_ratioDmgReportIn	0.3549	avgCommLink	0.4155
9	numReportInComm	0.3584	First_ratioKillReportIn	0.2914	First_ratioDmgTotalComm	0.3526	numCommLink	0.4134
10	First_ratioKillTotalComm!	0.354	First_ratioDmgNormalComm !	0.2783	numCommLink	0.3522	First_ratioKillNormalComm	0.4088
11	First_ratioKillReportIn	0.353	First_ratioKillNormalComm	0.2764	Second_totalComm	0.3476	First_ratioDmgNormalComm !	0.4047
12	First_ratioDmgReportIn	0.3505	Second_ratioDmgTotalCom m!	0.275	avgCommLink	0.3463	First_reportIn	0.3956
13	First_ratioDmgTotalComm	0.3475	First_ratioShotsReportIn1	0.2744	First_ratioShotsNormalComm	0.3415	1/3avgofreportin	0.395
14	First_ratioShotsNormalComm	0.3466	Third_shots	0.2695	First_ratioShotsReportIn1	0.3408	Third_totalComm	0.3888
15	Third_totalComm	0.3424	Third_ratioKillTotalComm!	0.2593	First_ratioShotsTotalComm	0.3362	First_ratioShotsNormalCom m	0.3885
16	First_ratioShotsReportIn1	0.3387	ReportIn_1/3_resourceLoad	0.2582	First_totalComm	0.3349	AgentLevel_Max_effectiveN etworkSize	0.3782
17	First_ratioShotsTotalComm	0.3312	ReportIn_2/3_resourceLoad	0.2582	numReportInComm	0.3208	First_ratioKillReportIn	0.3738
18	First_reportIn	0.3308	ReportIn_3/3_resourceLoad	0.2582	avgofReportInComm	0.3124	ReportIn_1/3_spanOfControl	0.3731
19	numNormalComm	0.3269	NormalComm_1/3_resource Load	0.2582	numNormalComm	0.3035	AgentLevel_Total_constraint	0.3716
20	AgentLevel_Max_effectiveNe tworkSize	0.3137	NormalComm_2/3_resource Load	0.2582	Third_totalComm	0.3032	avgofNormalComm	0.3702

Table C-9 Top 20 Correlations between *Players' total score* and Various Measures (Winners)

	Winners		Winners (Small)		Winners (Medium)	Winners (Large	e)
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	numSoldier	0.4892	numSoldier	0.3212	numSoldier	0.2452	AgentLevel_Min_simmeli anTies	-0.299
2	AgentLevel_Total_weakCo mponentMembers	0.4066	AgentLevel_Min_knowled geExclusivity	-0.294	lengthGame	-0.196	AgentLevel_Average_inf ormationCentrality1	-0.258
3	NormalComm_3/3_weakC omponentCount	0.377	AgentLevel_Average_kno wledgeExclusivity	-0.249	AgentLevel_Min_knowledg eExclusivity	-0.183	First_ratioKillNormalCom m	-0.237
4	NormalComm_2/3_weakC omponentCount	0.3762	AgentLevel_Total_weakC omponentMembers	0.2151	avgofNormalComm	-0.182	NormalComm_3/3_avera geDistance	-0.228
5	NormalComm_3/3_strong ComponentCount	0.3752	AgentLevel_Min_relativeE xpertise	-0.204	AgentLevel_Total_weakCo mponentMembers	0.1745	NormalComm_2/3_betw eennessCentralization1	-0.223
6	ReportIn_1/3_weakCompo nentCount	0.3709	AgentLevel_Average_relat iveExpertise	-0.204	3/3avgofnormalComm	-0.17	AgentLevel_Total_constr aint	-0.218
7	AgentLevel_Max_weakCo mponentMembers	0.3693	AgentLevel_Max_relative Expertise	-0.204	First_shots	-0.161	ReportIn_1/3_inDegreeC entralization	-0.218
8	NormalComm_2/3_strong ComponentCount	0.3674	AgentLevel_Total_closene ssCentrality	0.2028	NormalComm_3/3_weakC omponentCount	0.1575	AgentLevel_Average_inv erseClosenessCentrality	-0.212
9	NormalComm_1/3_weakC omponentCount	0.3659	Third_reportIn	0.1933	numNormalComm	-0.157	AgentLevel_Total_inDegr eeCentrality	-0.212
10	ReportIn_1/3_strongComp onentCount	0.3656	AgentLevel_Average_eige nvectorCentrality1	-0.19	2/3avgofnormalComm	-0.156	AgentLevel_Max_relative Similarity	-0.196
11	NormalComm_1/3_strong ComponentCount	0.3606	AgentLevel_Average_reso urceExclusivity	-0.182	NormalComm_3/3_strong ComponentCount	0.1458	NormalComm_2/3_stron gComponentCount	-0.196
12	NormalComm_3/3_diamet er	0.3526	AgentLevel_Min_resource Exclusivity	-0.176	NormalComm_2/3_weakC omponentCount	0.143	ReportIn_3/3_accessRed undancy	-0.194
13	ReportIn_1/3_diameter	0.3525	AgentLevel_Total_relative Similarity	0.1726	Third_normalComm	-0.143	NormalComm_3/3_acces sRedundancy	-0.194
14	ReportIn_2/3_diameter	0.3523	ratioSoldier	0.1708	Second_normalComm	-0.142	AgentLevel_Max_cogniti veLoad	-0.193
15	NormalComm_1/3_diamet er	0.3523	ratioMedic	-0.171	NormalComm_3/3_closene ssCentralization	-0.137	NormalComm_2/3_hierar chy1	-0.192
16	NormalComm_2/3_diamet er	0.3522	ReportIn_2/3_knowledgeR edundancy	0.17	ReportIn_1/3_weakCompo nentCount	0.136	AgentLevel_Average_co gnitiveLoad	-0.192
17	ReportIn_3/3_diameter	0.3522	NormalComm_3/3_knowle dgeRedundancy	0.17	AgentLevel_Max_weakCo mponentMembers	0.1344	ReportIn_3/3_minimumS peed	-0.19
18	ReportIn_2/3_knowledgeR edundancy	0.3474	NormalComm_2/3_knowle dgeRedundancy	0.17	NormalComm_3/3_totalDe greeCentralization1	-0.133	ReportIn_3/3_skipEdgeC ount	-0.185
19	NormalComm_3/3_knowle dgeRedundancy	0.3474	NormalComm_1/3_knowle dgeRedundancy	0.17	NormalComm_1/3_weakC omponentCount	0.1297	ReportIn_3/3_lateralEdg eCount	-0.185
20	NormalComm_2/3_knowle dgeRedundancy	0.3474	ReportIn_3/3_knowledgeR edundancy	0.17	NormalComm_2/3_strong ComponentCount	0.129	ReportIn_3/3_diameter	-0.184

Table C-10 Top 20 Correlations between *Players' total score* and Various Measures (Losers)

	Losers		Losers (Small)		Losers (Medium)		Losers (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	lengthGame	0.2023	lengthGame	0.1613	lengthGame	0.1794	lengthGame	0.2061
2	First_shots	0.1703	First_shots	0.1326	avgCommLink	0.1401	Second_totalComm	0.1554
3	numCommLink	0.166	numCommLink	0.1068	numCommLink	0.1368	First_shots	0.1532
4	Second_totalComm	0.1497	ReportIn_1/3_accessRedund ancy	0.1027	First_shots	0.1337	numReportInComm	0.1484
5	numReportInComm	0.1481	ReportIn_2/3_accessRedund ancy	0.1027	ReportIn_1/3_accessRedund ancy	0.1219	numCommLink	0.1464
6	First_totalComm	0.1475	ReportIn_3/3_accessRedund ancy	0.1027	ReportIn_2/3_accessRedund ancy	0.1219	First_totalComm	0.1449
7	ReportIn_1/3_accessRedund ancy	0.1418	NormalComm_1/3_accessR edundancy	0.1027	ReportIn_3/3_accessRedund ancy	0.1219	avgofReportInComm	0.1443
8	ReportIn_2/3_accessRedund ancy	0.1418	NormalComm_2/3_accessR edundancy	0.1027	NormalComm_1/3_accessRe dundancy	0.1219	avgCommLink	0.1409
9	ReportIn_3/3_accessRedund ancy	0.1418	NormalComm_3/3_accessR edundancy	0.1027	NormalComm_2/3_accessRe dundancy	0.1219	Second_reportIn	0.136
10	NormalComm_1/3_accessRe dundancy	0.1418	Second_shots	0.0928	NormalComm_3/3_accessRe dundancy	0.1219	ReportIn_1/3_resourceLoad	0.1345
11	NormalComm_2/3_accessRe dundancy	0.1418	avgCommLink	0.0877	First_totalComm	0.1054	ReportIn_2/3_resourceLoad	0.1345
12	NormalComm_3/3_accessRe dundancy	0.1418	numReportInComm	0.084	numReportInComm	0.1	ReportIn_3/3_resourceLoad	0.1345
13	numMedic	0.1299	First_ratioKillTotalComm!	0.0824	avgofReportInComm	0.0954	NormalComm_1/3_resource Load	0.1345
14	First_reportIn	0.1286	First_ratioKillReportIn	0.0823	Second_totalComm	0.0944	NormalComm_2/3_resource Load	0.1345
15	Second_reportIn	0.1279	First_totalComm	0.0816	First_reportIn	0.0926	NormalComm_3/3_resource Load	0.1345
16	Third_totalComm	0.1223	First_ratioKillNormalComm	0.0796	1/3avgofreportin	0.0888	numMedic	0.1339
17	AgentLevel_Total_effectiveN etworkSize	0.122	First_ratioShotsReportIn1	0.0789	Second_shots	0.0861	2/3avgofreportin	0.1314
18	numNormalComm	0.121	First_ratioShotsTotalComm	0.0779	AgentLevel_Total_effectiveN etworkSize	0.0811	ReportIn_2/3_lateralEdgeCo unt	0.1255
19	AgentLevel_Total_constraint	0.1204	First_ratioShotsNormalCom m	0.0763	AgentLevel_Total_outDegree Centrality	0.0809	First_reportIn	0.1233
20	AgentLevel_Total_personnel Cost	0.1196	First_reportIn	0.076	AgentLevel_Total_inDegreeC entrality	0.0809	Third_totalComm	0.1231

Table C-11 Top 20 Correlations between Average of the Players' total score and Various Measures (Winners)

	Winners		Winners (Small)		Winners (Medium)	Winners (Large	e)
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	lengthGame	-0.213	Third_reportIn	0.1316	First_shots	-0.208	AgentLevel_Min_simmeli anTies	-0.332
2	First_shots	-0.195	3/3avgofreportin	0.131	lengthGame	-0.205	AgentLevel_Average_inf ormationCentrality1	-0.288
3	numNormalComm	-0.185	ReportIn_3/3_networkLev els	0.1142	numNormalComm	-0.183	NormalComm_3/3_avera geDistance	-0.263
4	Third_normalComm	-0.171	ReportIn_3/3_averageDist ance	0.1118	avgofNormalComm	-0.177	NormalComm_2/3_betw eennessCentralization1	-0.259
5	Second_normalComm	-0.17	ReportIn_3/3_spanOfCont rol	0.1111	Third_normalComm	-0.17	First_ratioKillNormalCom m	-0.257
6	avgofNormalComm	-0.166	ReportIn_3/3_connectedn ess	0.1062	3/3avgofnormalComm	-0.166	AgentLevel_Total_inDegr eeCentrality	-0.241
7	First_totalComm	-0.164	ReportIn_3/3_averageSpe ed	0.1018	Second_normalComm	-0.161	AgentLevel_Average_inv erseClosenessCentrality	-0.241
8	NormalComm_2/3_averag eDistance	-0.153	ReportIn_3/3_totalDegree Centralization	0.0995	2/3avgofnormalComm	-0.157	AgentLevel_Total_constr aint	-0.237
9	NormalComm_2/3_spanOf Control	-0.153	ReportIn_3/3_closenessC entralization	0.0973	First_totalComm	-0.148	NormalComm_1/3_sequentialEdgeCount	-0.234
10	3/3avgofnormalComm	-0.153	ReportIn_3/3_minimumSp eed	0.0939	NormalComm_2/3_spanOf Control	-0.142	ReportIn_1/3_inDegreeC entralization	-0.233
11	NormalComm_2/3_networ kLevels	-0.15	ReportIn_3/3_inDegreeCe ntralization	0.0933	NormalComm_2/3_averag eDistance	-0.142	AgentLevel_Max_relative Similarity	-0.227
12	2/3avgofnormalComm	-0.149	ReportIn_3/3_outDegreeC entralization	0.0929	NormalComm_2/3_networ kLevels	-0.139	NormalComm_3/3_acces sRedundancy	-0.226
13	NormalComm_2/3_lateralE dgeCount	-0.138	Third_ratioReportInNormal Comm	0.0905	NormalComm_3/3_totalDe greeCentralization1	-0.136	AgentLevel_Min_inverse ClosenessCentrality	0.2223
14	First_reportIn	-0.135	avgofReportInComm	0.0896	NormalComm_2/3_totalDe greeCentralization1	-0.135	Second_ratioShotsReportIn	-0.221
15	NormalComm_3/3_lateralE dgeCount	-0.135	ReportIn_3/3_lateralEdge Count	0.0883	NormalComm_3/3_lateralE dgeCount	-0.134	NormalComm_2/3_hierar chy1	-0.219
16	NormalComm_2/3_averag eSpeed	-0.134	numReportInComm	0.0874	NormalComm_2/3_outDeg reeCentralization	-0.133	avgofNormalComm	0.2172
17	NormalComm_3/3_spanOf Control	-0.13	ReportIn_3/3_sequentialE dgeCount	0.0778	NormalComm_2/3_inDegr eeCentralization	-0.133	ReportIn_3/3_skipEdgeC ount	-0.217
18	NormalComm_2/3_totalDe greeCentralization1	-0.13	2/3avgofreportin	0.0734	NormalComm_3/3_networ kLevels	-0.133	NormalComm_1/3_weak ComponentCount	0.2151
19	NormalComm_3/3_networ kLevels	-0.129	ReportIn_3/3_reciprocalE dgeCount	0.0725	NormalComm_3/3_spanOf Control	-0.133	ReportIn_3/3_accessRed undancy	-0.214
20	Second_totalComm	-0.127	Second_reportIn	0.072	NormalComm_2/3_lateralE dgeCount	-0.131	AgentLevel_Max_cogniti veLoad	-0.213

Table C-12 Top 20 Correlations between Average of the Players' total score and Various Measures (Losers)

	Losers		Losers (Small)		Losers (Medium)		Losers (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	lengthGame	0.1604	lengthGame	0.1468	lengthGame	0.1761	lengthGame	0.1982
2	avgCommLink	0.1183	First_shots	0.1049	avgCommLink	0.1452	Second_totalComm	0.1445
3	First_shots	0.0973	numCommLink	0.0801	numCommLink	0.1282	First_shots	0.1443
4	numCommLink	0.0942	avgCommLink	0.0799	ReportIn_1/3_accessRedund ancy	0.1235	avgofReportInComm	0.1434
5	avgofReportInComm	0.0923	ReportIn_1/3_accessRedund ancy	0.0734	ReportIn_2/3_accessRedund ancy	0.1235	numReportInComm	0.1415
6	ReportIn_1/3_accessRedund ancy	0.0841	ReportIn_2/3_accessRedund ancy	0.0734	ReportIn_3/3_accessRedund ancy	0.1235	avgCommLink	0.1363
7	ReportIn_2/3_accessRedund ancy	0.0841	ReportIn_3/3_accessRedund ancy	0.0734	NormalComm_1/3_accessRe dundancy	0.1235	First_totalComm	0.1353
8	ReportIn_3/3_accessRedund ancy	0.0841	NormalComm_1/3_accessR edundancy	0.0734	NormalComm_2/3_accessRe dundancy	0.1235	numCommLink	0.1341
9	NormalComm_1/3_accessRe dundancy	0.0841	NormalComm_2/3_accessR edundancy	0.0734	NormalComm_3/3_accessRe dundancy	0.1235	2/3avgofreportin	0.1306
10	NormalComm_2/3_accessRe dundancy	0.0841	NormalComm_3/3_accessR edundancy	0.0734	First_shots	0.1226	Second_reportIn	0.13
11	NormalComm_3/3_accessRe dundancy	0.0841	Second_shots	0.0709	First_totalComm	0.0922	ReportIn_1/3_resourceLoad	0.1298
12	1/3avgofreportin	0.0821	avgofReportInComm	0.0676	avgofReportInComm	0.09	ReportIn_2/3_resourceLoad	0.1298
13	First_totalComm	0.0814	First_ratioKillTotalComm!	0.0659	numReportInComm	0.0847	ReportIn_3/3_resourceLoad	0.1298
14	numReportInComm	0.081	numReportInComm	0.0654	1/3avgofreportin	0.0841	NormalComm_1/3_resource Load	0.1298
15	Second_totalComm	0.0773	First_ratioKillReportIn	0.0649	Second_shots	0.08	NormalComm_2/3_resource Load	0.1298
16	ReportIn_1/3_resourceLoad	0.0772	First_ratioKillNormalComm	0.0633	Second_totalComm	0.0799	NormalComm_3/3_resource Load	0.1298
17	ReportIn_2/3_resourceLoad	0.0772	First_totalComm	0.0621	First_reportIn	0.0797	ratioMedic	0.1213
18	ReportIn_3/3_resourceLoad	0.0772	First_ratioShotsReportIn1	0.0615	AgentLevel_Max_personnelC ost	0.0795	ratioSoldier	-0.121
19	NormalComm_1/3_resourceL oad	0.0772	First_ratioShotsTotalComm	0.0609	AgentLevel_Average_totalDe greeCentrality1	0.0791	1/3avgofreportin	0.1199
20	NormalComm_2/3_resourceL oad	0.0772	1/3avgofreportin	0.0598	AgentLevel_Average_outDeg reeCentrality	0.0791	numMedic	0.1197

Table C-13 Top 20 Correlations between Average of new score and Various Measures (Winners)

	Winners		Winners (Small)		Winners (Medium)		Winners (Large)	
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	reportin_third_ weakcomponentcount	-0.486	reportin_third_ weakcomponentcount	-0.275	reportin_third_connectedness	0.455	reportin_third_ closenesscentralization	0.395
2	agentlevel_average_ weakcomponentmembers	-0.441	first_reportin	-0.219	reportin_third_ weakcomponentcount	-0.451	reportin_third_ weakcomponentcount	-0.395
3	reportin_all_ weakcomponentcount	-0.439	agentlevel_total_ weakcomponentmembers	-0.211	reportin_third_density	0.448	reportin_third_density	0.388
4	agentlevel_max_ weakcomponentmembers	-0.439	reportin_all_diameter	-0.209	reportin_third_ betweennesscentralization	0.444	reportin_third_networklevels	0.378
5	reportin_second_ weakcomponentcount	-0.435	reportin_first_diameter	-0.209	reportin_third_ closenesscentralization	0.432	reportin_third_averagedistance	0.367
6	agentlevel_total_ weakcomponentmembers	-0.423	reportin_second_diameter	-0.209	reportin_third_networklevels	0.426	reportin_third_ betweennesscentralization	0.346
7	reportin_all_diameter	-0.409	reportin_third_diameter	-0.209	reportin_third_averagedistance	0.376	reportin_third_connectedness	0.345
8	reportin_first_diameter	-0.409	normalcomm_all_diameter	-0.209	reportin_third_ clusteringcoefficient	0.329	second_dmg	0.321
9	reportin_second_diameter	-0.409	normalcomm_first_diameter	-0.209	reportin_third_ totaldegreecentralization	0.253	reportin_third_ totaldegreecentralization	0.310
10	reportin_third_diameter	-0.409	normalcomm_second_diameter	-0.209	thirdavgofreportin	0.250	second_kills	0.301
11	normalcomm_all_diameter	-0.409	normalcomm_third_diameter	-0.209	first_shots	-0.242	reportin_third_ clusteringcoefficient	0.292
12	normalcomm_first_diameter	-0.409	numplayer	-0.207	reportin_third_lateraledgecount	0.239	thirdavgofreportin	0.280
13	normalcomm_second_diameter	-0.409	numsoldier	-0.207	third_reportin	0.229	reportin_third_lateraledgecount	0.273
14	normalcomm_third_diameter	-0.409	numsurvive	-0.207	first_totalcomm	-0.223	agentlevel_max_ inverseclosenesscentrality	0.272
15	numplayer	-0.404	reportin_all_ strongcomponentcount	-0.207	reportin_second_ weakcomponentcount	-0.219	third_reportin	0.271
16	numsoldier	-0.404	reportin_all_ knowledgeredundancy	-0.207	reportin_third_ sequentialedgecount	0.217	reportin_third_ sequentialedgecount	0.267
17	numsurvive	-0.404	reportin_first_ strongcomponentcount	-0.207	reportin_third_spanofcontrol	0.217	reportin_third_spanofcontrol	0.267
18	reportin_all_knowledgeredundancy	-0.404	reportin_first_ knowledgeredundancy	-0.207	third_dmg	0.214	reportin_all_ weakcomponentcount	-0.266
19	reportin_first_strongcomponentcount	-0.404	reportin_second_ strongcomponentcount	-0.207	reportin_second_connectedness	0.208	reportin_all_ closenesscentralization	0.265
20	reportin_first_knowledgeredundancy	-0.404	reportin_second_ knowledgeredundancy	-0.207	reportin_second_ betweennesscentralization	0.207	agentlevel_max_ weakcomponentmembers	-0.263

Table C-14 Top 20 Correlations between Average of new score and Various Measures (Losers)

	Losers		Losers (Small)	Losers (Medium)		Losers (Large)		
Num	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.	Variable Name	Corr.
1	agentlevel_total_personnelcost	0.367	second_kills	0.359	first_dmg	0.337	third_reportin	0.476
2	third_kills	0.365	second_dmg	0.341	first_kills	0.323	thirdavgofreportin	0.472
3	agentlevel_total_cognitiveload	0.360	agentlevel_total_effectivenetworksize	0.317	first_shots	0.316	reportin_third_ networklevels	0.437
4	numplayer	0.357	agentlevel_max_nodelevels	0.305	reportin_third_ connectedness	0.250	reportin_third_ clusteringcoefficient	0.432
5	numsoldier	0.357	reportin_all_networklevels	0.305	reportin_third_ betweennesscentralization	0.243	reportin_third_density	0.429
6	numsurvive	0.357	agentlevel_average_interlockers	0.303	reportin_third_density	0.233	reportin_third_ closenesscentralization	0.426
7	reportin_all_ strongcomponentcount	0.357	agentlevel_total_nodelevels	0.302	reportin_third_ totaldegreecentralization	0.230	reportin_third_ connectedness	0.409
8	reportin_all_ knowledgeredundancy	0.357	second_shots	0.300	second_kills	0.228	reportin_third_ betweennesscentralization	0.398
9	reportin_first_ strongcomponentcount	0.357	reportin_all_lateraledgecount	0.293	reportin_third_ closenesscentralization	0.227	numreportincomm	0.395
10	reportin_first_ knowledgeredundancy	0.357	agentlevel_total_triadcount	0.290	reportin_third_networklevels	0.227	reportin_third_ averagedistance	0.394
11	reportin_second_ strongcomponentcount	0.357	first_kills	0.290	avgofreportincomm	0.220	avgofreportincomm	0.383
12	reportin_second_ knowledgeredundancy	0.357	reportin_all_averagedistance	0.287	third_kills	0.219	reportin_third_ lateraledgecount	0.378
13	reportin_third_ strongcomponentcount	0.357	first_dmg	0.286	thirdavgofreportin	0.217	reportin_third_ totaldegreecentralization	0.343
14	reportin_third_ knowledgeredundancy	0.357	numreportincomm	0.286	first_totalcomm	0.213	reportin_third_ weakcomponentcount	0.343
15	normalcomm_all_ strongcomponentcount	0.357	agentlevel_average_nodelevels	0.286	reportin_all_ clusteringcoefficient	0.211	third_kills	0.339
16	normalcomm_all_ knowledgeredundancy	0.357	agentlevel_max_effectivenetworksize	0.285	agentlevel_average_ triadcount	0.209	second_kills	0.330
17	normalcomm_first _strongcomponentcount	0.357	agentlevel_total_constraint	0.282	numreportincomm	0.209	third_totalcomm	0.317
18	normalcomm_first_ knowledgeredundancy	0.357	first_shots	0.280	third_reportin	0.208	agentlevel_max_radials	0.308
19	normalcomm_second_ strongcomponentcount	0.357	agentlevel_min_interlockers	0.278	reportin_third_ averagedistance	0.202	reportin_third_ sequentialedgecount	0.302
20	normalcomm_second_ knowledgeredundancy	0.357	agentlevel_average_effectivenetworksize	0.273	agentlevel_total_triadcount	0.202	reportin_third_ spanofcontrol	0.302

Appendix D – Beta Coefficient resulted from the regression analysis

Table D-1 Beta Coefficient calculated by regression analysis: ORA network level measures vs team received damage

Term	Estimate	t Ratio	Prob > t	Term	Estimate	t Ratio	Prob > t
averagedistance	150000.00	3.40	0.00	poolededgecount	NA	NA	NA
averagespeed	-2891.00	-4.90	0.00	reciprocaledgecount	-25.88	-2.28	0.02
betweennesscentralization	-2166.00	-3.31	0.00	sequentialedgecount	-98320	-3.34	0.00
closenesscentralization	9706.00	6.53	0.00	skipedgecount	NA	NA	NA
clusteringcoefficient	-304.80	-5.32	0.00	spanofcontrol	NA	NA	NA
connectedness	3356.00	5.82	0.00	strongcomponentcount	NA	NA	NA
density	-28820.00	-4.79	0.00	totaldegreecentralization	3811.00	5.31	0.00
diameter	147.80	63.41	<2e-16	transitivity	NA	NA	NA
efficiency	-112200	-3.43	0.00	upperboundedness	NA	NA	NA
hierarchy	111300	3.40	0.00	weakcomponentcount	NA	NA	NA
indegreecentralization	-119.60	-0.23	0.82	knowledgediversity	NA	NA	NA
interdependence	27.61	2.47	0.01	knowledgeload	NA	NA	NA
lateraledgecount	6.36	11.76	<2e-16	knowledgeredundancy	NA	NA	NA
minimumspeed	1273.00	4.53	0.00	accessredundancy	9.04	4.43	0.00
networklevels	-50290.00	-3.42	0.00	resourcediversity	-312.50	-21.88	<2e-16
outdegreecentralization	NA	NA	NA	resourceload	271.80	64.48	<2e-16

Table D-2 Beta Coefficient calculated by regression analysis: ORA network level measures vs team inflicted damage

Term	Estimate	t Ratio	Prob > t	Term	Estimate	t Ratio	Prob > t
averagedistance	15350.00	0.42	0.68	poolededgecount	NA	NA	NA
averagespeed	-4511.00	-9.13	<2e-16	reciprocaledgecount	153.00	16.11	<2e-16
betweennesscentralization	-1435.00	-2.62	0.01	sequentialedgecount	-7378.00	-0.30	0.76
closenesscentralization	7703.00	6.19	0.00	skipedgecount	NA	NA	NA
clusteringcoefficient	-29.34	-0.61	0.54	spanofcontrol	NA	NA	NA
connectedness	3456.00	7.16	0.00	strongcomponentcount	NA	NA	NA
density	-36320	-7.21	0.00	totaldegreecentralization	4704.00	7.83	0.00
diameter	59.40	30.45	<2e-16	transitivity	NA	NA	NA
efficiency	-11550	-0.42	0.67	upperboundedness	NA	NA	NA
hierarchy	11030.00	0.40	0.69	weakcomponentcount	NA	NA	NA
indegreecentralization	-861.60	-1.98	0.05	knowledgediversity	NA	NA	NA
interdependence	-104.60	-11.19	<2e-16	knowledgeload	NA	NA	NA
lateraledgecount	1.34	2.96	0.00	knowledgeredundancy	NA	NA	NA
minimumspeed	2094.00	8.90	<2e-16	accessredundancy	-6.63	-3.89	0.00
networklevels	-5340.00	-0.43	0.66	resourcediversity	-166.90	-14.01	<2e-16
outdegreecentralization	NA	NA	NA	resourceload	342.80	97.22	<2e-16

Appendix E – Summary of Principal Component Analysis

Table E-1 Summary of principal components analysis

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Standard deviation	8.321	3.3677	2.836	2.4949	1.9382	1.8687	1.7306	1.3153
Proportion of Variance	0.527	0.0864	0.0613	0.0474	0.0286	0.0266	0.0228	0.0132
Cumulative Proportion	0.527	0.6138	0.675	0.7224	0.751	0.7776	0.8004	0.8136
	PC9	PC10	PC11	PC12	PC13	PC14	PC15	
Standard deviation	1.2007	1.15	1.10857	1.10103	1.0529	1.02604	0.992	
Proportion of Variance	0.011	0.0101	0.00936	0.00923	0.00844	0.00802	0.0075	
Cumulative Proportion	0.8246	0.8347	0.84403	0.85326	0.86171	0.86973	0.8772	
	PC16	PC17	PC18	PC19	PC20	PC21	PC22	
Standard deviation	0.91984	0.86029	0.84809	0.81591	0.80514	0.76213	0.7513	
Proportion of Variance	0.00644	0.00564	0.00548	0.00507	0.00494	0.00442	0.0043	
Cumulative Proportion	0.88367	0.8893	0.89478	0.89985	0.90479	0.90921	0.9135	
	PC23	PC24	PC25	PC26	PC27	PC28	PC29	
Standard deviation	0.73107	0.69942	0.68164	0.63008	0.60906	0.6044	0.58833	
Proportion of Variance	0.00407	0.00373	0.00354	0.00302	0.00283	0.00278	0.00264	
Cumulative Proportion	0.91758	0.92131	0.92485	0.92787	0.9307	0.93348	0.93611	
	PC30	PC31	PC32	PC33	PC34	PC35	PC36	
Standard deviation	0.58003	0.55471	0.5441	0.52038	0.51465	0.4958	0.48981	
Proportion of Variance	0.00256	0.00234	0.00225	0.00206	0.00202	0.00187	0.00183	
Cumulative Proportion	0.93868	0.94102	0.94328	0.94534	0.94736	0.94923	0.95105	

Table E-2 Top 10 measures for each principal component in the perspective of the absolute weight to calculate the principal component

	Measure Name	PC1	Measure Name	PC2	Measure Name	PC3
		1.05E-		-1.54E-		-2.46E-
1	agentlevel_total_relativesimilarity	01	agentlevel_total_constraint	01	reportin_all_resourcediversity	01
		1.05E-		-1.54E-		-2.46E-
2	reportin_all_knowledgeload	01	agentlevel_max_constraint	01	reportin_first_resourcediversity	01
		1.05E-		-1.54E-		-2.46E-
3	reportin_first_knowledgeload	01	agentlevel_total_informationcentrality	01	reportin_second_resourcediversity	01
		1.05E-		-1.54E-		-2.46E-
4	reportin_second_knowledgeload	01	reportin_all_averagedistance	01	reportin_third_resourcediversity	01
		1.05E-		-1.54E-		-2.46E-
5	reportin_third_knowledgeload	01	reportin_all_sequentialedgecount	01	normalcomm_all_resourcediversity	01
		1.05E-		-1.54E-		-2.46E-
6	normalcomm_all_knowledgeload	01	reportin_all_spanofcontrol	01	normalcomm_first_resourcediversity	01
		1.05E-		-1.54E-		-2.46E-
7	normalcomm_first_knowledgeload	01	reportin_all_averagespeed	01	normalcomm_second_resourcediversity	01
		1.05E-		-1.53E-		-2.46E-
8	normalcomm_second_knowledgeload	01	agentlevel_average_constraint	01	normalcomm_third_resourcediversity	01
		1.05E-	-	1.53E-		-2.01E-
9	normalcomm_third_knowledgeload	01	agentlevel_max_eigenvectorcentrality	01	reportin_all_resourceload	01
		-9.91E-		-1.52E-		-2.01E-
10	agentlevel_total_knowledgeexclusivity	02	agentlevel_total_indegreecentrality	01	reportin_first_resourceload	01
	Measure Name	PC4	Measure Name	PC5		
		1.70E-		2.60E-		
1	normalcomm_all_averagedistance	01	third_ratiokillnormalcomm	01		
		1.70E-		2.60E-		
2	normalcomm_all_interdependence	01	third_ratiodmgnormalcomm	01		
		1.70E-		2.60E-		
3	normalcomm_all_sequentialedgecount	01	third_ratiokilltotalcomm	01		
		1.70E-		2.55E-		
4	normalcomm_all_spanofcontrol	01	third_ratioshotsnormalcomm	01		
		1.69E-		2.55E-		
5	normalcomm_all_averagespeed	01	third_ratiodmgtotalcomm	01		
		1.59E-		2.53E-		
6	normalcomm_all_reciprocaledgecount	01	third_ratioshotstotalcomm	01		
		1.56E-		2.03E-		
7	normalcomm_all_networklevels	01	thirdavgofnormalcomm	01		
		-1.54E-	-	1.53E-		
			1 .			
8	agentlevel_average_eigenvectorcentrality	01	avgofnormalcomm	01		
8	agentlevel_average_eigenvectorcentrality	01 -1.45E-	avgofnormalcomm	1.48E-		
8			avgofnormalcomm third_normalcomm			
	agentlevel_average_eigenvectorcentrality agentlevel_average_relativesimilarity	-1.45E-		1.48E-		

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